# WILL EFFICIENCY IN HEALTH EXPENDITURE IMPROVE CHILD HEALTH OUTCOMES? AN ENQUIRY ACROSS LMICs USING TWO-STAGE BOOTSTRAP DATA ENVELOPMENT ANALYSIS

**Pinak Sarkar* (PhD)**
Lal Bahadur Shastri Institute of Management, New Delhi, Delhi, 110075, India, Email: pinaksarkar12@gmail.com; pinaksarkar@lbsim.ac.in

**Nutan Shashi Tigga (PhD)**
Jindal School of Banking and Finance, O P Jindal University, Sonipat, Haryana 131029, India, Email: nutan.tigga@jgu.edu.in; tigga.nutan@gmail.com

*Corresponding author

**ABSTRACT:** This study measures the efficiency of health expenditures in improving child mortality outcomes, one of the targets of the Sustainable Development Goals (SDG). Bootstrap data envelopment analysis was used to evaluate the efficiency of 127 low- and middle-income countries (LMICs) from 2010 to 2019. We found that 45 percent of the LMICs operated at decreasing returns to scale (DRS), implying that an increase in inputs could generate only a smaller increase in health outcomes, whereas 53 percent exhibited increasing returns to scale, indicating that an increase in health expenditure could lead to a greater increase in health outcomes. The findings of the study also have greater policy implications. It suggests that countries which perform at DRS could deliberate on reallocating resources to improve their health outcomes since these countries may not benefit from an increase in the input level as their output will not increase at the same rate. Therefore, governments should focus on improving efficiency rather than increasing health expenditure, thereby enabling the achievement of the SDG target.

**KEYWORDS:** Health expenditure; LMICs; sustainable development goals; bootstrap data envelopment analysis; bootstrap truncated regression.

## 1. INTRODUCTION

Developed countries have made substantial progress in improving child health outcomes; however, in most of the low-and middle-income countries (LMICs), this continues to be a major concern. In 2021 alone, a total of five million children died before their fifth birthday, of which 2.3 million died in just the first month of life, mostly due to preventable communicable and infectious diseases. Globally, the under-five mortality rate (U5MR) is 38 per 1,000 live births, whereas it is 74 per 1,000 live births in sub-Saharan Africa and 67 per 1,000 live births in low-income countries, whereas it is five per 1,000 live births in high-income countries (HICs) (United Nations Inter-agency Group for Child Mortality Estimation (UN IGME), 2023). A similar trend was observed for the neonatal mortality rate (NNMR), which was 27 per 1,000 live births in sub-Saharan Africa compared with 18 per 1,000 live births in World (UN IGME, 2023).

Improving child survival is imperative, as it is a vital indicator of a thriving society and one of the targets of sustainable development goals (SDGs). SDG-3.2 calls for all countries to reduce the NNMR to as low as 12 per 1,000 live births, and the U5MR to as low as 25 per 1,000 live births by 2030. Undoubtedly, progress to meet the SDGs is advancing; however, not at the required pace. Unfortunately, no single country will be able to achieve all the 17 SDGs by 2030 as indicated in the latest SDG Index and Dashboard (SDGI&D) report (Sachs *et al*., 2022). As far as SDG-3.2 is concerned, 54 countries will not achieve the target for the U5MR, and 63 countries will miss the target for the NNMR. Of the 54 countries that are likely to miss the U5MR target, 40 are in sub-Saharan Africa, 47 are classified as low- or lower-middle-income and approximately 25 are classified as fragile and belong to conflict-affected regions. Similarly, 43 countries out of 63 countries that are likely to miss the NNMR target are in sub-Saharan Africa; 51 countries belong to the low- or lower-middle-income category and 26 countries belong to fragile and conflict-affected regions (UN IGME, 2023).

One of the challenges faced by the LMICs for improving health outcomes is the supply-side constraints, particularly limited health expenditures, poor health infrastructure, and a lack of health personnel. Studies in the context of sub-Saharan African countries have shown that healthcare expenditure is a crucial component for reducing infant and neonatal mortality (Novignon and Lawanson, 2017; Chireshe and Ocran, 2020; Kiross *et al*., 2020). However, along with the inadequate public spending, the associated health system inefficiencies in these countries poses a greater challenge. As is common in the LMICs, inefficiencies arise from shortages, weak management, and poor distribution of resources (Mills, 2014), unlike in the high-income countries, where inefficiency is a result of excessive use of inputs (Chisholm and Evans, 2010). The International Monetary Fund (2019) indicated that a substantial proportion of public spending is wasted due to the misallocation of funds, poor quality of public services, waste of resources, the crowding out of private spending, and corruption, leading to the estimation of additional spending of ten percentage points of gross domestic product (GDP) in LMICs and two percentage points in emerging market economics (Cristóbal *et al*., 2021). The COVID-19 pandemic clearly reflects the inadequacy and inefficiency faced by the health systems across the world, particularly in the LMICs. Therefore, an assessment of health spending efficiency for achieving child health outcomes across the LMICs is important.

The two most commonly used approaches to measure the efficiency of health expenditure are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The former is a parametric approach that allows for making statistical inferences, whereas the latter is a non-parametric approach that requires no functional form. Despite this shortcoming, DEA is a widely used approach because it can accommodate multiple inputs and outputs simultaneously, unlike SFA. In a health system, various health resources are utilised to achieve multiple health outcomes; hence, DEA is a more suitable approach.

Measuring health spending efficiency to reduce child mortality across the LMICs remains unexplored. Additionally, with the SDGs approaching, the necessity of evaluating the performance of health outcomes across the LMICs motivated the present study. Here, DEA is used to measure the efficiency of health expenditure in achieving two SDG targets. Instead of the traditional DEA, a bootstrap DEA is employed to make sensible statistical inferences. Furthermore, following Simar and Wilson (2007), a bootstrap truncated regression based on the maximum likelihood method is used to identify the environmental factors contributing to the inefficiencies in achieving the desired target. By considering the period between 2010 and 2019, we intend to highlight the decadal change in efficiency across LMICs. However, owing to data limitations, the effect of COVID-19 could not be captured. Given that reducing child mortality is one of the SDG targets, this study also contributes towards understanding the linkages between efficiency and SDG outcomes.

The paper is organised as follows. Section 2 discusses the literature on the efficiency of health expenditures. Section 3 discusses the methodology. Section 4 presents the details of the data and variables used.

Section 5 discusses the results, Section 6 covers the discussion, and Section 7 contains the conclusion, limitations, and future scope of the study.

### *Efficiency of Health Expenditure*

Measuring efficiency has garnered considerable attention over the last two decades at the sectoral level (e.g., health, education, industry) via parametric and nonparametric approaches. A study by Gupta and Verhoeven (2001) measured health and education spending efficiency for a sample of 85 countries for the period between 1984 and 1995, via the free disposal hull (FDH) approach. The health input they took was per capita health spending by the government in purchasing power parity (PPP), while the health outputs considered were life expectancy, infant mortality, diphtheria, pertussis, and tetanus (DPT) and measles immunisation rates. They reported that the African economies are less efficient in providing health services than Asian and Western Hemisphere countries are. Afonso and St. Aubyn (2005) also estimated the efficiency of health and education expenditures for a group of OECD countries via FDH and DEA. They used the number of inpatient beds and the doctors and nurses density (per thousand population) as inputs and the infant mortality rate, life expectancy, and maternal mortality rate as health outputs. They reported that three countries—Korea, Japan, and Sweden—were efficient irrespective of the sector or method considered. Another study by Herrera and Pang (2005) covering 140 countries estimated health and education expenditure efficiencies for 1996–2002 via FDH and DEA techniques. They took public expenditure, private expenditure, and literacy of adults as health inputs and life expectancy at birth, DPT immunisation, measles immunisation, and disability adjusted life expectancy (DALE) as outputs. They found that most of the countries that were inefficient could produce the same level of outputs by utilising half of the inputs. Rayp and De Sijpe (2007) used DEA to examine government expenditure efficiency across 52 developing countries using DEA. Central government expenditures per capita (in PPP) were considered as inputs and infant mortality, immunisation against measles, youth illiteracy rates, secondary enrollment, and government effectiveness were outputs. The findings suggested that output indicators could be increased by 50 percent, keeping the level of inputs constant. Afonso and St. Aubyn (2011) evaluated the efficiency of health services in OECD countries in terms of life expectancy,infant survival rate, potential years of life not lost as outputs, and doctors, nurses, beds and MRI units as inputs. The study concluded that countries could increase their efficiency by 40 percent by using the existing amount of resources. Chai *et al*. (2019) estimated the efficiency of health expenditure via bootstrap DEA in 31 provinces of mainland China in 2015. The health outcomes selected were infant survival rates, maternal survival rates, and healthy life years, while the inputs were health expenditures and the density of medical personnel and hospital beds. They found that approximately 60 percent of the provinces were operating at a decreasing return to scale (DRS), implying that efficiency gain could be possible only through downsizing the scale of operation. Another paper by Ahmed *et al*. (2019) measured the efficiency of health expenditures via DEA, Censored Tobit regression, and a smoothed bootstrap model across 46 Asian countries. This study used per capita health expenditure as the input variable and healthy life expectancy at birth and infant mortality per 1,000 live births as the output variables. The findings show that the efficient countries (Cyprus, Japan, and Singapore) were mainly from the high-income group and that only one country (Bangladesh) belonged to the lower middle-income group. Garcia-Escribano (2022), in their recent study, estimated the health spending efficiency across countries via bias-corrected DEA. The output variable was life expectancy, and the input variable was per capita health spending. They found that a sizable difference across countries exists in the efficiency scores achieved, particularly among emerging and developing countries, compared with advanced economies. A recent study by Tigga and Sarkar (2024) in the context of India evaluated the health system efficiency and productivity during the pre- and post-reform via using bootstrap DEA and bootstrap Malmquist Productivity Index (MPI). The study revealed that inefficiencies increased in the postreform period.

The literature survey indicates that most studies have focused on single countries, whereas efficiency measurements across a group of countries are scarce. The DEA methodology is a relative measurement of efficiency; hence, it provides a better understanding of countries' performance against the frontier. Such an analysis can signal the countries that have moved away from the frontier and indicate the excess or shortage of the resources used to attain health outcomes.

## 3. METHODOLOGY

The term efficiency or technical efficiency (TE) is a normative measure that is widely used in the economics literature. TE is the ratio of actual output to the maximum output attainable (often called a frontier) for a given amount of inputs (Farrell, 1957). In the context of a health system, it can be defined as the attained level of output compared with the maximum level of output, which can be achieved via the given amount of resources or inputs (Tandon *et al*., 2003). The efficiency literature generally discusses two approaches: nonparametric (deterministic) and parametric (stochastic) frontier approaches. DEA is the most common approach of the former category, while in the latter, it is the SFA approach. DEA is a widely used measure, as it does not require any specification of any functional form to run the model, unlike the latter; hence, it is a widely used analytical approach in healthcare and related fields (Emrouznejad and Yang, 2018).

DEA is a mathematical programming technique based on linear programming (LP) that measures the relative performance of a group of organisational units such as firms, plants, and entities, also known as decision making units (DMUs). Two models are extensively used within the DEA framework: the Charnes, Cooper, and Rhodes (CCR) model (Charnes *et al*., 1978) and the Banker, Charnes, and Cooper (BCC) model (Banker *et al*., 1984). The former assumes a production technology with constant returns to scale (CRS), whereas the latter assumes variable returns to scale (VRS). The CCR model calculates *overall technical efficiency* (OTE) scores, and the BCC model provides *pure technical efficiency* (PTE) scores and *Scale Efficiency* (SE) scores. Thus, the SE for each DMU is the ratio of the OTE score to the PTE score, i.e.,

$$SE = \frac{OTE}{PTE}$$

### *Output-Oriented Approach and Returns to Scale*

A DEA model can either be input-oriented or output-oriented. The primary objective of an input-oriented model is to minimise the inputs used to obtain a certain amount of output, whereas in the case of an output-oriented model, it aims to maximise the outputs with a given amount of input. Another important concept in the production function is the RTS, which explains the long-run relationship between the inputs and outputs.

The original CCR model assumed a production technology with CRS. This was rather restrictive; CRS is often unlikely to hold in many realistic scenarios. To address this shortcoming, the BCC model was developed, which allows for VRS. There are two dimensions of VRS: increasing returns to scale (IRS) and decreasing returns to scale (DRS). In the IRS, a one percent increase in inputs results in a greater than one percent increase in outputs, and in the DRS, an increase in inputs of one percent results in a less than one percent increase in outputs (Cheng *et al*., 2015).

In the present study, the output-oriented model operating under VRS is found to be more appropriate, as the objective is to maximise health outcomes given the fixed level of inputs. Additionally, in a health system, the input levels are usually fixed in the short run; hence, reducing them may not be feasible (Evans *et al*., 2001; Jacobs *et al*., 2006). Hence, the output-oriented model is more realistic and reflects real-world situations (Cheng *et al*., 2015).

Assume a set of $DMU_j$ (j=1, 2,…n) to be evaluated and define $(x_{1j}\ldots.x_{mj})$ as the input vector of $DMU_j$ with input weight vectors $(v_1\ldots,v_m)$ and $(y_{1j}\ldots,y_{qj})$ as the output vector of with output weight vectors $(u_1\ldots,v_q)$. Assume that each $DMU_j$ consumes $x_{ij}$ amount of input *i* to produce $y_{rj}$ amount of output *r*, and that the input and output of $DMU_k$ (k=1,...,n) to be evaluated are, $(x_{1k},...,x_{mk})$ and $(y_{1k},...,y_{qk})$, where $x_{ik} \geq 0$ and $y_{rk} \geq 0$.
Let $\mu_r = t_{ur}$ and $v_i = t_{vi}$, where t = $(\sum_{i=1}^{m} v_i x_{ik})^{-1}$. The output-oriented BCC-DEA model has the following form:

Maximise $\sum_{i=1}^{m} v_i x_{ik} + v_0)$

Subject to

$$
\begin{cases}
\displaystyle\sum_{r=1}^{q} \mu_r y_{rj} + \sum_{i=1}^{m} v_i x_{ij} + v_0 \leq 0 \ (\mathrm{j} = 1, \ldots, \mathrm{n}), \\
\displaystyle\sum_{r=1}^{q} \mu_r y_{rk} = 1, \\
\mu_r \geq 0 \ (\mathrm{r} = 1, \ldots, \mathrm{q}), v_i \geq 0 \ (\mathrm{i} = 1, \ldots, \mathrm{m}), v_0 \in \mathbb{R}
\end{cases}
$$

For a set of *n* DMUs, a standard DEA model is solved *n* times i.e., one for each DMU. Efficiency scores equal to 1 indicate an efficient unit, whereas scores less than 1 indicate inefficient units.

### *Bootstrap DEA and Bootstrapped Truncated Regression*

Traditional DEA models are sensitive to the choice of inputs and outputs and fail to accommodate the effect of any nondiscretionary factors that may impact the production function, thereby resulting in bias efficiency scores. To correct this bias, a bootstrapping technique introduced by Simar and Wilson (2000) was used, which provides bias-corrected efficiency scores. The efficiency estimates were obtained via MaxDEA Ultra (Version 9) with 2,000 repetitions.

DEA models are nonparametric in nature; hence, the scores do not have any statistical significance and do not explain the sources for inefficiency. Ray (1991) and Coelli *et al*. (2005) suggested the two-stage approach, in which the DEA scores estimated in the first stage are regressed on the environmental factors in the second stage. However, Simar and Wilson (2007) argued that the DEA efficiency estimates themselves are by construction serially correlated. To address this problem, they proposed an alternative estimation and statistical inference procedure based on a double-bootstrap approach. Following Simar and Wilson (2007), a bootstrapped truncated regression (Algorithm #1), with 2,000 repetitions, was performed in Stata V.17.

## 4. DATA

### *Inputs and Outputs*

The literature and availability of data guide the selection of inputs and outputs. For the study, one input and two outputs were selected. The input variable selected for the study is current health expenditure expressed as a percentage of GDP. The two outputs selected are U5MR and the NNMR. In the DEA model, the outputs are measured such that ‘more is better’. However, in the case of the two outputs selected, the same implication is not feasible as ‘less is better’. Hence, a transformation of NNMR and U5MR is used. Using the following formula, the two outputs are converted:

$$\text{Neonatal Survival Rate (NNSR)} = \frac{1000 - \text{NNMR}}{\text{NNMR}}$$

$$\text{Under 5 Survival Rate (U5SR)} = \frac{1000 - \text{U5MR}}{\text{U5MR}}$$

Data on inputs and outputs for 127 LMICs were obtained from the World Bank database for the period of 2010–2019. The data period could not be extended beyond 2019 to analyse the effect of COVID-19 to maintain a certain number of DMUs or countries. The choice of environmental factors is guided by the previous literature and data availability. The four environmental factors included for the bootstrapped truncated regression are access to clean fuels and technologies for cooking (% of population), access to electricity (% of the population), out-of-pocket expenditure (% of current health expenditure), and female labour force (% of the total labour force). The data for these variables are also obtained from the World Bank database.

## 5. RESULTS

### *Descriptive Statistics*

Table 1 shows the descriptive statistics of the variables used in the study. There is considerable variability in the inputs and outputs across the LMICs. For example, the NNSR ranges between 23 per 1,000 live births and 908 per 1,000 live births, and a similar variation is observed for the U5SR. Montenegro had the highest U5SR, whereas Belarus had the highest NNSR. A similar pattern is apparent for the input variable, current health expenditure, as a proportion of GDP which ranges from two percent in Djibouti to 24 percent in Tuvalu, indicating stark disparity in health spending across the LMICs.

### *Efficiency Estimates*

The bias-corrected OTE, PTE, and SE scores are obtained via an output-oriented bootstrap DEA model for 127 LMICs. The efficiency scores obtained vary between 0 and 1, where 1 implies that the country is efficient in health spending and lies on the production frontier; scores less than 1 indicate the existence of inefficiency. The average bias-corrected PTE was 0.1057, indicating that the country's health system has been operating highly inefficiently. The mean level of SE was 0.8029, indicating a scale inefficiency level of 19.71 percent. As a result, the bias-corrected OTE was 0.1265 (95% CI 0.1748 to 0.3074). The results show that only one country

(Belarus) exhibited CRS i.e., it operated at most productive scale size (MPSS). A country with the same efficiency score under both constant and variable returns to scale assumption has CRS. In contrast, 58 countries (45 percent) operated at DRS, implying that an increase in inputs could generate only a smaller increase in health outcomes. Alternatively, 68 countries (53 percent) presented an IRS, meaning that an increase in inputs could generate a greater increase in health outcomes. Furthermore, the scale efficiency was assessed across the income groups. The total LMICs included 24 low-income countries (LICs), 53 lower middle-income countries (LMCs), and 50 upper middle-income countries (UMCs). Out of the 24 LICs, 10 performed at DRS, while the remaining 14 operated at IRS. Likewise, in the case of LMCs, 19 operated at the DRS, whereas the remaining at IRS. In the case of UMCs, 27 performed at DRS and 22 at IRS. Countries exhibiting an IRS could improve their efficiency score by operating at a larger scale and using more inputs to achieve better outcomes. In contrast, countries operating at a DRS could increase their technical efficiency by using fewer inputs to achieve better outcomes.

**Table 1.** Summary Statistics of the Variables. Source: Calculated by Authors using WDI data.

| Variables | Average | SD | Maximum | Minimum |
|---|---|---|---|---|
| **Outputs** | | | | |
| Neo-natal survival rate (Per 1000 live births) | 104.42 | 122.32 | 908.09 | 23.21 |
| Under-five survival rate (Per 1000 live births) | 53.25 | 55.62 | 369.37 | 7.55 |
| **Inputs** | | | | |
| Current health expenditure (% of GDP) | 6.10 | 3.04 | 23.96 | 1.80 |
| **Environmental factors** | | | | |
| Access to clean fuels and technologies for cooking (% of population) | 52.24 | 37.37 | 100.00 | 0.00 |
| Access to electricity (% of population) | 78.16 | 27.95 | 100.00 | 6.71 |
| Out-of-pocket expenditure (% of current health expenditure) | 36.17 | 19.92 | 84.79 | 0.10 |
| Labor force, female (% of the total labor force) | 41.64 | 8.49 | 63.93 | 13.85 |

Figure 1 shows the bootstrap OTE scores across the LMICs categorised into six tiers. The highest efficiency score was achieved by Montenegro (0.573), while Sierra Leone had the lowest efficiency score (0.012). The three countries with the lowest efficiency scores belong to the low-income group. These were Liberia, Central African Republic, and Sierra Leone. Contrarily, the top three countries with the highest efficiency scores belong to the upper middle-income group (Montenegro and Belarus) and the lower middle-income group (Sri Lanka). Notably, Sri Lanka, a lower middle-income country, ranked third with an efficiency score of 0.4847.

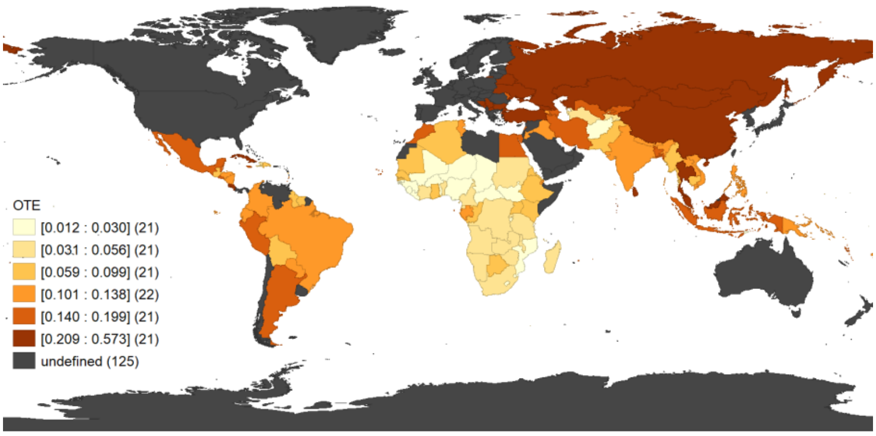


**Figure 1.** Overall Technical Scores Across LMICs. Source: Made by Authors using the estimated results.

Table 2 shows the heterogeneity in the efficiency scores across the World Bank's income classification of countries. The highest bias-corrected PTE was obtained by the UMCs (0.233: 95% CI 0.318-0.531), followed by the LMCs (0.011: 95% CI 0.212-0.805) and LICs (0.044: 95% CI 0.065-0.116). Therefore, the potential improvement if the countries operate at maximum efficiency with the given amount of health expenditure would be 95.62 percent, 98.92 percent, and 76.71 percent for LICs, LMCs, and UMCs, respectively.

**Table 2.** Mean Bias-corrected Efficiency Scores Based on World Banks's Income Groups. Source: Calculated by Authors using WDI data.

| **Income groups** | **Mean** | **SD** | **CI [95%] Lower Bound** | **CI [95%] Upper Bound** | **Potential Improvement (%)** |
|---|---|---|---|---|---|
| Low-income (LICs) | 0.044 | 0.029 | 0.065 | 0.116 | 95.62 |
| Lower Middle-income (LMCs) | 0.011 | 0.931 | 0.212 | 0.805 | 98.92 |
| Upper Middle-income (UMCs) | 0.233 | 0.160 | 0.318 | 0.531 | 76.71 |

Separate DEA models were estimated for each period to generate 10 sets of efficiency scores. Figure 2 shows the bias-corrected efficiency scores for the period between 2010 and 2019. From 2010 to2019, the mean efficiency was 14.60 percent, suggesting that the LMICs could save 85.39 percent of health expenditures to achieve the same level of health outcomes if they followed their peers. The average efficiency score was highest in 2015, which declined over the subsequent years. By 2019, the efficiency score was lower than the average of 2010. The heterogeneity in the efficiency level across the World Bank's income groups is depicted in Figure 3. Clearly, the highest average bias-corrected scores were obtained by UMC compared with those of LICs and LMCs throughout the study period from 2010 to 2019. The efficiency of health spending in LICs has been constant over the years, whereas for the LMCs, a sharp decline was noted after 2013 and again in 2017. In contrast, health spending efficiency in the UMCs sharply increased in 2013.

### *Bootstrap Truncated Regression*

In the second stage, a bootstrap truncated regression is performed to account for the effect of environmental factors in OTE. Table 3 shows the results from the Simar-Wilson bias-corrected truncated regression analysis. Three variables were statistically significant and were associated with greater efficiency in health spending. The estimated coefficient of access to electricity is strongly associated with efficiency. Furthermore, female labour force participation was positively related to health spending efficiency. Finally, out-of-pocket expenditures are negatively associated, suggesting that the higher the proportion of out-of-pocket expenditure

(OOP) in current health expenditures is, the greater the level of inefficiency.

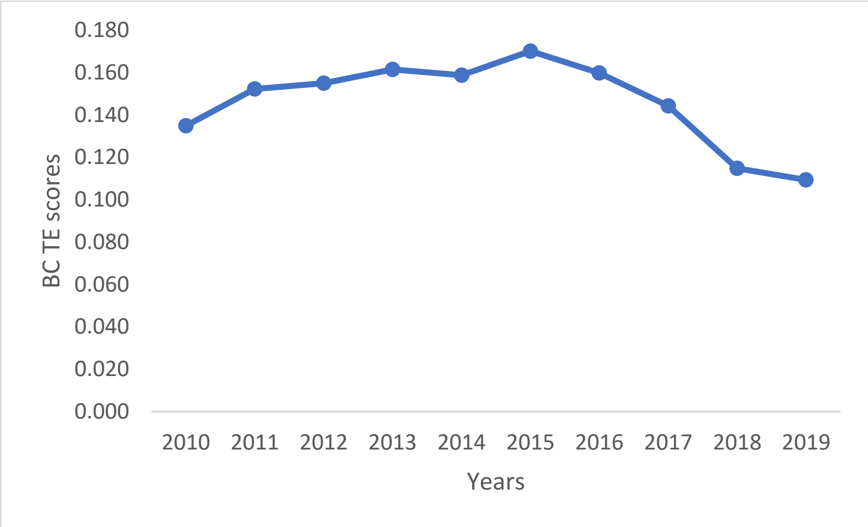


**Figure 2.** Average Bias-corrected Technical Efficiency Scores for LMICs Across Years. Source: Made by Authors using the estimated results.

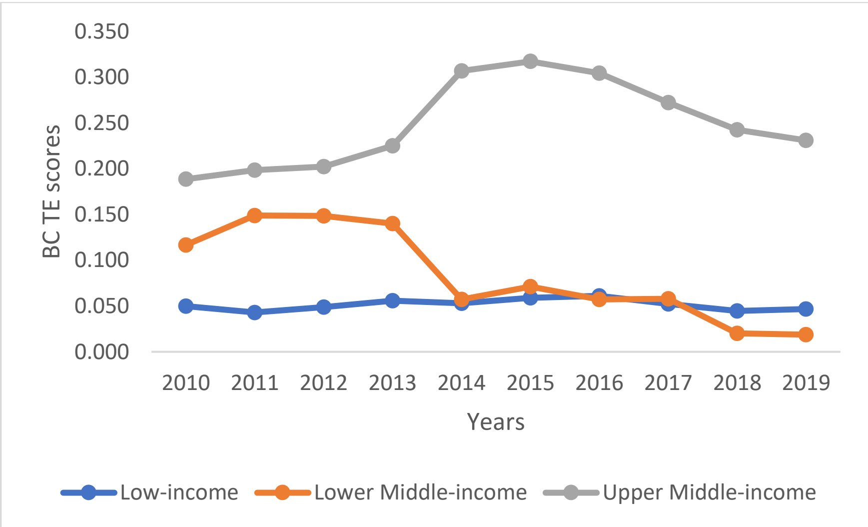


**Figure 3.** Biased-corrected Technical Efficiency Score Across World Bank's Income Group. Source: Made by Authors using the estimated results.

**Table 3.** Bootstrap Truncated Regression Results. Source: Calculated by Authors using WDI data.

| | Observed Coeff. | Bootstrap Std. Err. | P>z | CI [95%] Lower Bound | Upper Bound |
|---|---|---|---|---|---|
| Labour force, female | 0.003* | 0.002 | 0.095 | -0.001 | 0.007 |
| Out-of-pocket expenditure | -0.002** | 0.001 | 0.023 | -0.004 | 0.000 |
| Access to electricity | 0.010*** | 0.002 | 0.000 | 0.006 | 0.013 |
| Access to clean fuels and technologies for cooking | 0.000 | 0.001 | 0.710 | -0.001 | 0.001 |
| Constant | -0.848 | 0.191 | 0.000 | -1.181 | -0.442 |
| Sigma | 0.125 | (0.0136) | 0.000 | 0.946 | 0.147 |

*** p<0.01, ** p<0.05, * p<0.1

## 6. DISCUSSION

This study explores the technical efficiency and scale efficiency of health expenditures in improving two health outcomes viz. U5MR and NNMR across 127 LMICs from 2010 to 2019. It also examines the role of environmental factors in influencing OTE scores. The findings suggest that if the identified inefficient countries could improve their health spending patterns, they could achieve better health outcomes.

The results show that the average bias-corrected PTE was 0.1057, indicating high inefficiency across the countries and the mean SE of 0.8029, indicating a scale inefficiency level of 19.71 percent. The average bias-corrected OTE was significantly low at 0.1265 (95% CI 0.1748-0.3074) and quite heterogeneous across the countries. Countries belonging to UMC tend to have relatively high OTE, compared with countries belonging to LICs, which performed less efficiently, especially those in sub-Saharan Africa. Some of the UMCs also experienced high inefficiency. For example, 11 UMCs had bias-corrected OTE values less than 0.127, meaning that the resources invested in these countries did not have the desired impact on the health outcomes. However, the greater concern was countries which were from the group of LICs with poor outcomes and poor OTE scores were of greater concern.

In our study, the low OTE across LMICs was a result of high scale inefficiency. The findings show that only one country from the UMCs (Belarus) operated at most productive scale size (MPSS). Notably, it has the lowest NNMR and a significantly low U5MR, which the country is achieving using the health expenditures which was five percent of its GDP. In addition, 45 percent operated at DRS, meaning that an increase in inputs could generate only a smaller increase in health outcomes. Moreover, 53 percent operated at the IRS, meaning that an increase in inputs could generate a greater increase in health outcomes. Across income groups, it is seen that out of the 24 LICs, 10 performed at DRS, whereas the remaining 14 operated at IRS. In the case of LMCs, out of 53, 19 operated at DRS, whereas the remaining 34 operated at IRS and out of 50 UMCs, 27 performed at DRS and 22 at IRS. Countries exhibiting DRSs are not efficiently utilising the given level of inputs to attain the current output level. If they are to increase the input level, their output will not increase at the same rate. However, countries operating at the IRS could scale up operations which may lead to greater efficiency, keeping in mind the efficient utilisation and minimum waste of resources. Coincidentally, previous studies have shown diminishing returns of health inputs on health outcomes. A study in 30 European countries revealed that 26 of 30 countries exhibited DRS, and only four countries were scale efficient (Asandului *et al*., 2014). Cetin and Bahce (2016), in their study, reported that DRS characterised 11 out of 26 OECD countries. Chai *et al*. (2019), in their study in China, reported that 18 out of 31 provinces operated at DRS, whereas 13 operated at MPSS.

The average PTE values across the World Bank's income classification of countries reveal that UMCs achieved the highest value, followed by LMCs and LICs. Similar findings have been reported by previous studies, which report that developed countries are more efficient at utilising their health expenditures than less developed countries (Grosskopf *et al*., 2006; Ahmed *et al*., 2019; Arhin *et al*., 2023). From 2010 to 2019, the mean efficiency was 14.60 percent, which suggests that the countries could save 85.39 percent of health expenditures to achieve the same level of health outcomes if they performed as their peers did. The technical efficiency score declined from 0.134 in 2010 to 0.109 in 2019. This decline could be associated with various factors, such as a high disease burden and shortage of financial resources (Sun *et al*. 2017), weak management and poor allocation and/or use of resources (Mills, 2014; Babalola and Moodley, 2020), and therefore resulting in low efficiency in health spending.

On the basis of previous studies and the availability of data, few environmental factors were selected. To observe the heterogeneity in OTE, Simar and Wilson (2007) employed bootstrapped truncated regression to examine the factors influencing the variation. The results suggest that a unit increase in access to electricity could lead to a 0.10 unit increase in health outcomes, keeping the level of health expenditure constant. Similar findings were reported by Asghar *et al.* (2023). Female labour force participation was also positively related to health spending efficiency, which is consistent with the findings of Dwomoh *et al*. (2019). The negative association between out-of-pocket expenditures and efficiency indicates that the higher the proportion of OOP in current health expenditures is, the greater the level of inefficiency, as reported earlier by Chai *et al*. (2019).

Finally, the high level of scale inefficiency (19.71 percent) suggests that the LMICs should identify the optimum operational scale, rather than merely increasing the health resources, in this case health expenditures, to improve the two health outcomes. The reallocation of resources, especially in countries which perform at DRS, could result in better health outcomes, thereby enabling the achievement of the SDG target.

## 7. CONCLUSION

Improving the efficiency of health spending is critical for reducing the NNMR and the U5MR across LMICs. The reallocation of resources and the emulation of peer countries could improve the health spending efficiency. The findings also suggest that if countries operate at maximum efficiency with the given amount of health expenditure, the potential improvements would be 95.7 percent for LICs, 98.4 percent for LMCs, and 76.9 percent for UMCs. Moreover, improving access to electricity and female labour force participation and reducing out-of-pocket expenditures could reduce inefficiency in health spending and improve the NNMR and the U5MR, such that the SDGs are achieved by the end of the target period. In LMICs, limited financial resources, high disease burdens, and low efficiency suggest that those countries have limited capacity to transfer available funds to improve the health of the targeted population, which further reduces the pace of progress in moving towards their committed goals, such as, SDGs.

The policy recommendation that emerges from the study is that the countries should reflect in reallocating resources. It is a crucial strategy to optimise health systems, especially amidst budget constraints and growing healthcare demands. Since resource reallocation is closely related to income levels, the countries must make strategies accordingly. For instance, the HICs and MICs may have the financial resources to invest in health technology and innovation and streamline operations to reduce waste. The LICs on the other hand could think of reallocating their resources towards essential services that may have a greater impact on public health, such as maternal and child health. Additionally, they could also direct their resources towards preventive public health interventions, such as better access to clean water and sanitation, nutrition, and health education.

The present study has its own limitations. One of the most important limitations is the choice of the time period. Health expenditures and health outcomes have undergone significant transitions during the COVID-19 pandemic; however, due to the unavailability of data, the recent period was not included. Second, although the literature discusses various factors that could influence the efficiency of health expenditure, a limited number of factors are incorporated in the study given data availability across all the LMICs.

## REFERENCES

Ahmed, S., Hasan, M.Z., MacLennan, M., Dorin, F., Ahmed, M.W., Hasan, M.M., Hasan, S.M., Islam, M.T., and Khan, J.A.M. (2019) Measuring the efficiency of health systems in Asia: a data envelopment analysis. *BMJ Open,* 9(3), 1–12, https://bmjopen.bmj.com/content/9/3/e022155, doi:10.1136/bmjopen-2018-022155.

Afonso, A., and St. Aubyn, M. (2005) Non-parametric approaches to education and health efficiency in OECD countries. *Journal of Applied Economics,* 8(2), 227–246, https://doi.org/10.1080/15140326.2005.12040626.

Afonso, A., and St. Aubyn, M. (2011) Assessing health efficiency across countries with a two-step and bootstrap analysis. *Applied Economics Letters,* 18(15), 1427–1430, https://doi.org/10.1080/13504851.2010.541149.

Arhin, K., Frimpong, A.O., Boso, R., and Acheampong. K. (2023) A double bootstrap data envelopment analysis model for evaluating malaria spending efficiency in Sub-Saharan Africa. *Healthcare Analytics*, 3, 100137, https://doi.org/10.1016/j.health.2023.100137.

Asandului, L., Roman, M., and Fatulescu, P. (2014) The efficiency of healthcare systems in Europe: A data envelopment analysis approach. *Procedia Economics and Finance*, 10**,** 261–268, https://doi.org/10.1016/S2212-5671(14)00301-3.

Asghar, N., Amjad, M.A., and Rehman, H.U. (2023) Analysing the impact of access to electricity and biomass energy consumption on infant mortality rate: A global perspective. *Environmental Science and Pollution Research*, 30(11), 29550–29565, https://doi.org/10.1007/s11356-022-24144-9.

Babalola, T. K., and Moodley, I. (2020) Assessing the efficiency of health-care facilities in Sub-Saharan Africa: A systematic review. *Health Services Research and Managerial Epidemiology*, 7, https://doi.org/10.1177/2333392820919.

Banker, R.D., Charnes, A., and Cooper, W.W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078–92, https://www.jstor.org/stable/2631725.

Cetin, V.R., and Bahce, S. (2016) Measuring the efficiency of health systems of OECD countries by data envelopment analysis. *Applied Economics*. 48(37), 3497–507, https://doi.org/10.1080/00036846.2016.1139682.

Chai, P., Zhang, Y., Zhou, M., Liu, S., and Kinfu, Y. (2019) Technical and scale efficiency of provincial health systems in China: A bootstrapping data envelopment analysis. *BMJ Open*, 9, e027539, http://dx.doi.org/10.1136/bmjopen-2018-027539.

Charnes, A., Cooper, W.W., and Rhodes, E. (1978) Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6), 429–44, https://doi.org/10.1016/0377-2217(78)90138-8.

Cheng, Z., Tao, H., Cai, M., Lin, H., Lin, X., Shu, Q., and Zhang, R. (2015) Technical efficiency and productivity of Chinese county hospitals: An exploratory study in Henan province, China. *BMJ Open*, 5, e007267, http://dx.doi.org/10.1136/bmjopen-2014-007267.

Chireshe, J., and Ocran, M.K. (2020) Health care expenditure and health outcomes in sub-Saharan African countries. *African Development Review*, 32(3), 349–361, https://doi.org/10.1111/1467-8268.12444.

Chisholm, D., and Evans, D.B. (2010) *Improving Health System Efficiency as a Means of Moving Towards Universal Coverage*. World Health Report, Geneva.

Coelli, T., Rao, D.S.P., O'Donnell, C.J., and Battese, G.E. (2005) *An Introduction to Efficiency and Productivity Analysis* (4th ed), Springer, New York.

Cristóbal, J., Ehrenstein, M., Domínguez-Ramos, A., Galán-Martín, A., Pozo, C., Margallo, M., Aldaco, R., Jiménez, L., Irabien, A., and Guillén-Gosálbez, G. (2021) Unravelling the links between public spending and Sustainable Development Goals: Insights from data envelopment analysis. *Science of Total Environment*, 786, 147459, https://doi.org/10.1016/j.scitotenv.2021.147459.

Dwomoh, D., Amuasi, S., Agyabeng, K., Incoom, G., Alhassan, Y., and Yawson, A.E. (2019) Understanding the determinants of infant and under-five mortality rates: A multivariate decomposition analysis of demographic and health surveys in Ghana, 2003, 2008 and 2014. *BMJ Global Health*, 4**,** e001658, http://dx.doi.org/10.1136/bmjgh-2019-001658.

Emrouznejad A., and Yang, G.L. (2018) A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio Economic Planning Sciences*, 61, 4–8. https://doi.org/10.1016/j.seps.2017.01.008.

Evans, D.B., Tandon, A., Murray, C.J.L., and Lauer, J.A. (2001) Comparative efficiency of national health systems: Cross national econometric analysis. *BMJ* 323, 307–10, https://doi.org/10.1136/bmj.323.7308.307.

Farrell, M. J. (1957) The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society Series A: Statistics in Society* 120 (3): 253–281. https://doi.org/10. 2307/2343100.

Garcia-Escribano, M., Juarros, P., and Mogues, T. (2022) Patterns and Drivers of Health Spending Efficiency. IMF Working Papers 22/48. International Monetary Fund, Washington.

Grosskopf , S., Self, S., and Zaim, O. (2006) Estimating the efficiency of the system of healthcare financing in achieving better health. *Applied Economics*, 38(13), 1477–1488, https://doi.org/10.1080/00036840500424798.

Gupta, S., and Verhoeven, M. (2001) The efficiency of government expenditure: Experiences in Africa. *Journal of Policy Modelling*, 23(4), 433–67, https://doi.org/10.1016/S0161-8938(00)00036-3.

Herrera, S., and Pang, G. (2005) Efficiency of Public Spending in Developing Countries: An Efficiency Frontier Approach. World

Bank Policy Research Working Paper No: WPS3645. World Bank, Washington, DC.

International Monetary Fund (IMF). (2019) Fiscal policy and development: Human, social, and physical investment for the SDGs. IMF Staff Discussion Note SDN/19/03.

Jacobs, R., Smith, P.C., and Street, A. (2006) *Measuring Efficiency in Health Care: Analytic Techniques and Health Policy*, Cambridge University Press, United Kingdom.

Kiross, G.T., Chojenta, C., Barker, D., and Loxton, D. (2020) The effects of health expenditure on infant mortality in sub-Saharan Africa: Evidence from panel data analysis. *Health Economics Review*, 10(5), https://doi.org/10.1186/s13561-020-00262-3.

Mills, A. (2014) Health care systems in low-and middle-income countries. *New England Journal of Medicine,* 370(6), 552–7.

Novignon, J., and Lawanson, A.O. (2017) Health expenditure and child health outcomes in Sub-Saharan Africa. *African Review of Economics and Finance*, 9(1), 96–121.

Ray, S.C. (1991) Resource-use efficiency in public schools: A study of Connecticut data. *Management Science*, 37, 1620–1628.

Rayp, G., and Sijpe, N.V.D. (2007) Measuring and explaining government efficiency in developing countries. *Journal of Development Studies*, 43(2), 360–381, https://doi.org/10.1080/00220380601125230.

Sachs, J., Lafortune, G., Kroll, C., Fuller, G., and Woelm, F. (2022) *From Crisis to Sustainable Development: The SDGs as Roadmap to 2030 and Beyond. Sustainable Development Report*, Cambridge University Press, United Kingdom.

Simar, L., and Wilson, P.W. (2000) A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics*, 27(6), 779–802, https://doi.org/10.1080/02664760050081951.

Simar, L., and Wilson, P.W. (2007) Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1), 31–64, https://doi.org/10.1016/j.jeconom.2005.07.009.

Sun, D., Ahn, H., Lievens, T., and Zeng, W. (2017) Evaluation of the performance of national health systems in 2004-2011: An analysis of 173 countries. *PLoS One,* 12(3), https://doi.org/10.1371/journal.pone.0173346.

Tandon, A., Lauer, J. A., Evans, D. B., and Murray, C. J. (2003). Health system efficiency: concepts. Health systems performance assessment: debates, methods and empiricism, 683-691.

Tigga, N. S., and Sarkar, P. (2024). Has the efficiency and productivity of the health system in India improved during post-policy period? Application of the bootstrap data envelopment analysis and Malmquist productivity index. *Applied Economics*, 57(11), 1239–1256, https://doi.org/10.1080/00036846.2024.2311759.

United Nations Inter-agency Group for Child Mortality Estimation (UN IGME). (2023) *Levels and Trends in Child Mortality: Report 2022, Estimates Developed by the United Nations Inter-agency Group for Child Mortality Estimation*, United Nations Children's Fund, New York.

World Bank (2022) World Data Bank. World Development Indicators Retrieved November 10, 2022 from https://databank.worldbank.org/source/world-development-indicators.