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HEALTH SPENDING EFFICIENCY IN DEVELOPING ASIA

Donna Faye Bajaro, Yothin Jinjarak, Yuho Myoda, Donghyun Park, and Pilipinas Quising

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ABSTRACT

The coronavirus disease (COVID-19) pandemic placed health-care systems around the world under great stress. The sharp increase in demand for health care highlighted the importance of efficient health spending. The negative impact of the pandemic on global economic growth further strengthened the case for efficient health spending. In this paper, we examine health spending efficiency in developing Asia. Using data envelopment analysis, we find that East Asia has the highest average output- and input-oriented technical efficiency scores among the subregions. Universal health coverage service coverage index and population density have the strongest effect on health spending efficiency. In addition, using the novel framework of macro-level efficiency analysis, we find that developing Asia falls short of optimal total health expenditures. Caucasus and Central Asia has the highest average allocative efficiency score among the subregions. Overall, developing Asia has substantial room for improvement in both technical and allocative efficiency.

Keywords: health spending, data envelopment analysis, technical efficiency, allocative efficiency

JEL codes: C10, C60, H51, I10

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1. Introduction

The coronavirus disease (COVID-19) pandemic was an unprecedented global health and economic crisis. Developing Asia too felt the impact of the pandemic on its health systems and economies. More specifically, COVID-19 placed health systems in the region and the rest of the world under a great deal of stress as the demand for health services rose sharply. Given the difficulty of ramping up the capacity of the health system to devote more resources in a short time period, the pandemic highlighted the need for efficient health spending. That is, given the constraints to increasing health spending in the short run, the efficiency with which a country spends its resources will go a long way toward determining how well it copes with pandemics and other major shocks. At the same time, the deceleration of global growth during the pandemic and the consequent reduction of resources available for the health system further strengthens the case for more efficient health spending. Finally, in the medium to long term, climate change, population aging, and other structural challenges will pose huge fiscal demands on the region's governments, underlining the need for efficient public spending on health care. For all these reasons, now is an opportune time to empirically examine the efficiency of health spending in developing Asia.¹

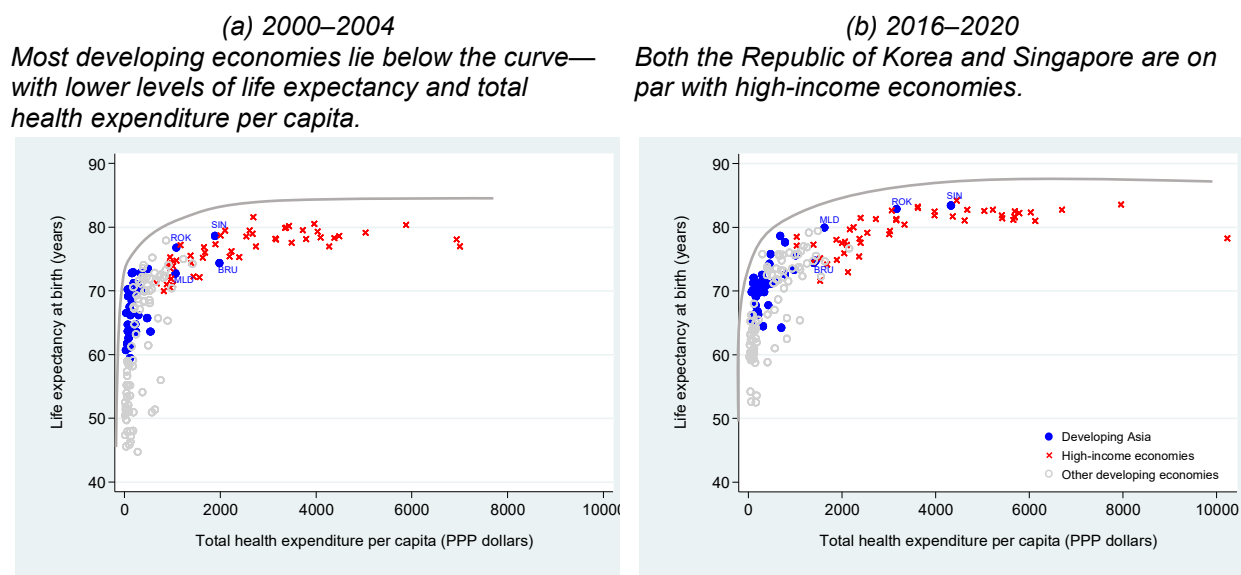
This paper aims to assess health spending efficiency by evaluating the link between life expectancy and health expenditure. Figure 1 presents the 5-year averages of life expectancy at birth and total health expenditure per capita.² Even after 2 decades, most economies lie below the curve—with lower levels of life expectancy and total health expenditure per capita. The Republic of Korea (ROK) and Singapore are way above developing economies and even some high-income economies. Interestingly, Maldives surpasses Brunei Darussalam in terms of life

¹ While we are interested in the efficiency of health spending, we show the current state of health spending in developing Asia in Appendix Figure A.1. The appendix can be accessed at <http://dx.doi.org/10.22617/WPS230471-2>.

² Total health expenditure refers to the sum of government and private health expenditures from domestic sources. Current health expenditure, on the other hand, is the sum of health expenditures from domestic and foreign sources. The analysis using current health expenditure is in the Appendix.

expectancy even though they spend about an equal amount on total health expenditure per capita. One can ask: Which economies exhibit health spending efficiency? What can we learn from them?

Figure 1: Life expectancy at birth (years) and total health expenditure per capita (PPP dollars), 2000–2004 vs. 2016–2020



BRU = Brunei Darussalam, MLD = Maldives, PPP = purchasing power parity, ROK = Republic of Korea, SIN = Singapore.

Notes: The global sample covers 168 economies, comprising 37 developing Asian economies—Caucasus and Central Asia has 7, East Asia 3, South Asia 7, Southeast Asia 10, and the Pacific 10. Total health expenditure per capita are 2017 real values.

Source: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

With the aid of Dynamic Benchmarking Tool 2.0, developed by Samer Matta (World Bank Group, senior economist), we compare developing Asia based on the trends of life expectancy at birth, and total and government health expenditures per capita and identify the comparator economies using income classification as the only criterion. Appendix Figure A.2 illustrates dynamic benchmarking of the three indicators from 2015 to 2020. The red dashed line represents the country of interest, and the green dashed line is the median. The comparator economies (or structural peers) of the country of interest are listed at the bottom of each panel. For example, the

comparators of the Philippines from developing Asia are India, the Lao People's Democratic Republic (Lao PDR), Samoa, and Uzbekistan, and from the rest of world are Angola, Bolivia, Cabo Verde, El Salvador, Eswatini, and Morocco. The peers of Singapore are Bermuda; Brunei Darussalam; the Cayman Islands; Ireland; Luxembourg; Macau, China; Norway; Qatar; Switzerland; and United Arab Emirates. The peers of the ROK are Aruba, Canada, Cyprus, Czechia, Finland, France, Israel, Italy, Japan, and Malta.

One significant feature of our paper is that it tackles both technical and allocative efficiency. Technical efficiency is the life expectancy that can be achieved given the actual amount of health expenditure; or the amount of health expenditure that can be reduced given the actual level of life expectancy. This study deploys two estimation methods: (i) data envelopment analysis (DEA), a non-parametric linear programming; and (ii) stochastic frontier analysis (SFA), a parametric approach like regression analysis. Note, however, that the focus of our discussion is DEA results and we report the SFA results in the Appendix. Allocative efficiency, on the other hand, is the amount of health expenditure that should be spent to maximize life expectancy considering other competing societal priorities such as education and infrastructure. This study adapts the novel framework of Chen et al. (2021), and Hall and Jones (2007).

2. Literature Review on Health Spending Efficiency

Several studies apply DEA in the estimation of technical efficiency. However, the literature lacks differentiation between input- and output-oriented technical efficiency and overlooks allocative efficiency. In this paper, we seek to bridge the gap in the literature by estimating both technical and allocative efficiency of health spending.

The most recent literature on health spending efficiency evolves in the context of the COVID-19 pandemic. Kuzior et al. (2022) assess the economic efficiency of public health systems in 22 economies. They construct integrated efficiency indices of more than 40 indicators, including domestic government health expenditure as a share of gross domestic product (GDP), and apply frontier DEA in estimating the efficiency of each economy classified according to their operating health care model. Their findings reveal that the efficiency scores of Thailand's transitional health care model is 92%, while India's market health care model is 44% and 100% for the People's Republic of China (PRC).

Other studies focus solely on the efficiency of health expenditure. Shi et al. (2022) estimate the health expenditure efficiency of 30 provinces in the PRC from 1999 to 2018 using a hybrid meta-frontier DEA model. Within the national common frontier, the PRC's Eastern and Central regions have average scores of 67% and 51%, respectively, while the Western region's is 46%. At the provincial level, Beijing (Eastern region) scores the highest at 86%, and Xinjiang (Western region) at 43%. The three regions in the PRC have a large room for improvement. In addition, Guo et al. (2021) calculate the total factor productivity (TFP) or efficiency of health care expenditure in 31 provinces in the PRC from 2004 to 2020 using Malmquist DEA and determine the factors affecting the efficiency using Tobit regression model. The average TFP before the implementation of the New Health Care Reform (NHCR) in 2009 is 0.83 and 0.91 after implementation. Even if the TFP is less than 1.0 before and after the NHCR, significant improvement happens after the NHCR. The Tobit regression reveals that GDP per capita,

population density, and NHCR are positive determinants of government health care expenditure efficiency.

Lionel (2015) assesses the health spending efficiency of 151 economies from 2005 to 2011 using DEA and determines the factors that affect efficiency using Tobit regression. In the application of DEA, the input is health expenditure per capita, and the outputs are life expectancy and infant survival rate. Using the sample of high-income economies, Japan and Singapore score 100%. For reference, the United States (US), which has the highest health expenditure per capita, ranks 38th, scoring only 94%. The lead scorers (i.e., located on the frontier) are Fiji and Malaysia in upper-middle-income economies; Pakistan, Sri Lanka, and Viet Nam in lower-middle-income; and Bangladesh and Nepal in low-income. Additionally, the Tobit estimation unveils that GDP per capita, population density, ageing composition, carbon dioxide emission, corruption control, and government effectiveness are significant factors of health expenditure efficiency. Ahmed et al. (2019) estimate the output-oriented technical efficiency score of health expenditure per capita in 46 Asian economies using the DEA variable returns to scale (VRS) model, with healthy life expectancy at birth and infant mortality as outputs. Bangladesh, Japan, and Singapore have scores of 100%. The average efficiency score of Asian economies is 92%, wherein high-income economies score 93% and all others 91%. Tobit regression demonstrates that primary education completion and population density are positive determinants of efficiency, while bed density is a negative factor.

Herrera and Ouedraogo (2018) calculate the input and output technical efficiency scores of various countries using public expenditure on health as input and various health indicators as output. Appendix Figure A.3 summarizes the point estimates of developing Asian economies using disability-adjusted life expectancy as output. In terms of input efficiency score, developing Asia has an average score of 54%, suggesting the region could have reduced health spending by 46% to reap the same health outcome. At the sub-regional level, East Asia scores the highest at 68%, followed by Caucasus and Central Asia, and Southeast Asia at 54%. Compared to other

regions, developing Asia is more efficient than Africa (49%) and somewhat comparable with Latin America (56%). For output efficiency, as with other regions, developing Asia scores a higher average at 85%, indicating health outlays achieve 15% short of the potential outcome attainable with efficient government spending. At the sub-regional level, East Asia still scores the highest at 91%, followed by Caucasus and Central Asia, and Southeast Asia at 87%. Developing Asia performs better than Africa (73%) but worse than Latin America (91%). A more recent study by Clements, Gupta, and Jalles (2021) similarly used DEA to measure developing Asia's potential gain from improved health expenditure. On average, they find that Asian economies could have improved health outcome (in terms of better life expectancy) by around 7% had public spending been efficient. Against other regions, Asia has the highest potential gain with efficient spending compared to Latin America (6%) and advanced economies (4%).

Several literature focus on the overall efficiency of the health systems, instead of health spending. Yang et al. (2022) evaluate the overall efficiency, resource allocation efficiency, and service operation efficiency of 31 provincial health systems in the PRC from 2009 to 2020 using a two-stage network DEA model. Resource allocation efficiency is 68%, while service operation efficiency is 84%. Due to low resource allocation, the overall efficiency of provincial health systems in the PRC achieves a low score of 58%. Moreover, Gavurova, Kocisova, and Sopko (2021) analyze the health systems efficiency in Organisation for Economic Co-operation and Development (OECD) economies for selected years 2000, 2008, and 2016. They estimate the overall efficiency and the efficiency of interconnected areas such as public and medical care using dynamic network data envelopment analysis (DNDEA). Using the VRS model, the efficiency score of the ROK is 100%.

While preponderance of studies measuring technical efficiency are available, few have paid attention to allocative efficiency. At the macro-level, Chen et al. (2021) empirically measure allocative efficiency in 15 economies, which include India and the PRC, by estimating the optimal health spending allocation based on the framework adapted from Hall and Jones (2007). Using

2015 data, their study reveals that 14 of the 15 economies evaluated, with the US as an exemption, could benefit from increased resources directed toward health. India and the PRC have the largest gap between the actual and optimal health spending.

3. Framework of Health Spending Efficiency

This section examines health spending based on the conceptual underpinnings of technical and allocative efficiency, as well as the corresponding estimation approaches used in the literature.

3.1. Technical Efficiency

Technical efficiency pertains to the extent to which fixed amount of inputs can achieve the maximum possible results.³ Spending is considered efficient when the highest possible health outcome—when there is no room for improvement—is attained given available budget. Figure 2 depicts technical efficiency using an illustrative sample of economies with given health budget on the horizontal axis and health outcome on the vertical axis. The points along the blue curve (points *B* and *C*) are considered the most technically efficient economies since it is impossible for them to produce better health outcomes using the available health budget. The economies below and to the right of the frontier (point *A*) are deemed less efficient and have the capacity to be technically efficient by moving either upward or leftward until these economies lie on the blue curve. Hence, the blue curve that envelopes all economies is referred to as [technical] efficiency frontier.

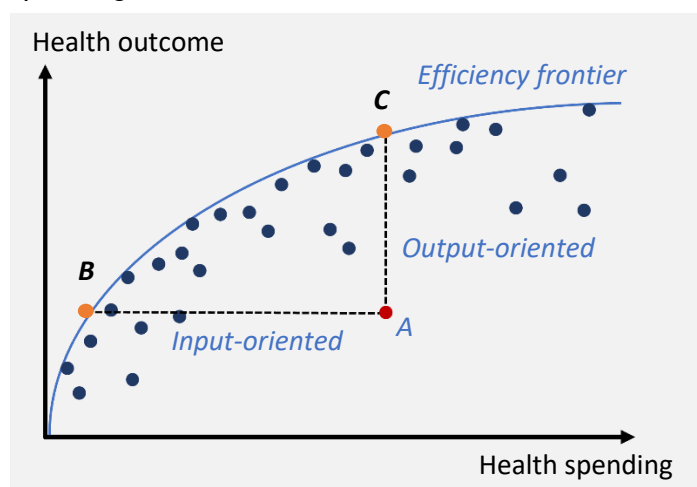
A country's spending efficiency is determined by the distance from the frontier. The two ways to look at technical efficiency are:

³ This study explores DEA and SFA, which are both widely used methods in estimating technical efficiency. However, the discussion mainly focuses on DEA. Interested readers may refer to the summary differences between DEA and SFA in Appendix Table A.1; derivations, econometric model, and estimation of SFA in Appendix A.1; variable definitions and sources in Appendix Table A.2; estimation results in Appendix Table A.3; and technical efficiency scores in Appendix Figure A.4.

- (i) **Output-oriented.** This pertains to the extent to which health outcome can be improved with the same level of health resources. It is measured by the vertical distance from the efficiency frontier, \overline{CA} .
- (ii) **Input-oriented.** This refers to the extent to which outlays can be reduced to achieve the same level of health outcome. It is measured by the horizontal distance from the efficiency frontier, \overline{BA} .

Figure 2: Technical efficiency

Efficiency frontier shows the maximum health outcome feasible under efficient health spending.



Source: Adapted from Zhang, Tone, and Lu (2018).

3.1.1. Data Envelopment Analysis

DEA is a benchmarking tool that measures the efficiency of decision-making units (DMUs). It is a non-parametric approach that uses linear programming to approximate a hull that represents efficiency frontier and enfolds the combinations of observed inputs and outputs as tightly as possible (Ji and Lee 2010, Huguenin 2012). DMUs located on the frontier have efficiency scores of 1.0 (or 100%) and are the benchmark of inefficient DMUs (scores below 1.0) for improvement. No DMU can go above the frontier. Note, however, that DEA computes the relative and not the absolute efficiency scores. This means that DMUs located on the frontier scoring 1.0 can still

enhance their efficiency (Huguenin 2012), which in effect will induce the efficiency frontier to shift upwards.

DEA has several variations. It can be differentiated between output- and input-oriented models and between constant returns to scale (CRS) and VRS. CRS assumes that all DMUs operate at optimal scale while VRS does not. In other words, CRS accounts for the proportional relationship between input and output. VRS allows for increasing, decreasing, or constant returns. The imposition of equations (4) and (9) differentiates VRS from CRS.

In this paper, we estimate both output- and input-oriented models using VRS. For brevity, we present the dual (not the primal) equations of VRS linear programming models. The VRS output-oriented primal model maximizes the output with the given level of input. To lessen the computational burden, the VRS output-oriented dual model:

$$\max \phi_i \tag{1}$$

subject to:

$$\phi_i y_i - \sum_{j=1}^n \lambda_j y_j \leq 0 \tag{2}$$

$$x_i - \sum_{j=1}^n \lambda_j x_j \geq 0 \tag{3}$$

$$\sum_{j=1}^n \lambda_j = 1 \tag{4}$$

$$\lambda_j \geq 0 \quad \forall j = 1, \dots, n \tag{5}$$

where ϕ_i is the increase in output of firm i that can be achieved when input is held constant, and $\frac{1}{\phi_i}$ represents the technical efficiency of firm i . y_i and x_i are the output and the input of firm i , respectively. y_j and x_j are the output and the input of firm j where $j = 1, 2, \dots, n$. λ_j is the associated weighting of outputs and inputs of firm j . Equation (4) is the additional restriction in the VRS dual model (not included in the constraints of CRS) to signify the convexity constraint, which is equivalent to the measure of return to scale in the VRS primal model.

The VRS input-oriented primal model minimizes input with the given level of output. To lessen the computational burden, the VRS input-oriented dual model:

$$\min \theta_i \tag{6}$$

subject to:

$$y_i - \sum_{j=1}^n \lambda_j y_j \leq 0 \tag{7}$$

$$\theta_i x_i - \sum_{j=1}^n \lambda_j x_j \geq 0 \tag{8}$$

$$\sum_{j=1}^n \lambda_j = 1 \tag{9}$$

$$\lambda_j \geq 0 \quad \forall j = 1, \dots, n \tag{10}$$

where θ_i represents the technical efficiency of firm i , and λ_j is the associated weighting of outputs and inputs of firm j . y_i and x_i are the output and the input of firm i , respectively. y_j and x_j are the output and the input of firm j where $j = 1, 2, \dots, n$. The constraints (7) to (10) in VRS input-oriented dual model resemble the constraints (2) to (5) in VRS output-oriented dual model.

Following the models discussed above, we use one output (y) and one input (x) in estimating both VRS output-oriented and input-oriented models. In our estimations, life expectancy at birth is the output, and total/government health expenditures per capita is the input.⁴ We perform sensitivity analysis using four different outputs. This is discussed further in the succeeding sub-sections.

3.2. Allocative Efficiency

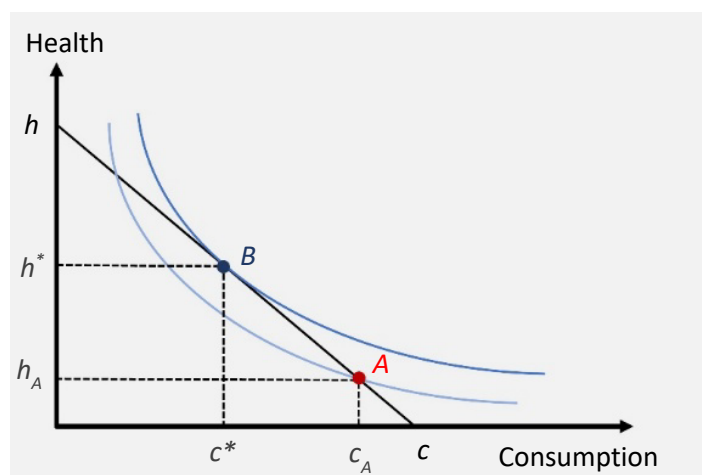
Allocative efficiency is concerned with the mix of limited resources to achieve the attainable maximum result. Within the health sector, it deals with the configuration of health input that produces the best possible desired health outcome. At the macro-level, it pertains to the optimal share of health in the economy-wide resources, given other competing priorities, that yields welfare-maximizing solution for the society.

⁴ The estimation command in Stata is **dea**.

Figure 3 illustrates economy-wide allocative efficiency in health, with consumption as an alternative societal priority. The budget line \overline{hc} is the set of all combinations of health and consumption that an economy can manage to afford within the available budget. The indifference curve is the set of combinations of health and consumption that yield the same level of satisfaction to the society. To maximize welfare from health and consumption, decision-makers need to determine how to best apportion society's limited resources between the two choices. Conceptually, allocative efficiency is realized when limited resources (represented by the budget line \overline{hc}) and societal objective (represented by the utility curve signifying the preference between the two choices) are best aligned with one another. This is shown as point B where the budget line is tangent to the utility curve. Redirecting the resources toward the optimal allocation, depicted as a movement from point A to point B where health share is higher and consumption lower, represents a welfare improvement for the society (demonstrated as the attainment of higher utility level from the light blue to blue utility curve).

Figure 3: Allocative efficiency

Realizing optimal health allocation needs alignment with other spending priorities and economy-wide objectives.



Source: Adapted from McKenzie and Lee (2010).

3.2.1. Macro-level Analysis

The macro-level analysis examines whether an economy underspends or overspends on health. This also determines the gap between the actual and optimal spending. The novel framework behind this analysis is adapted from Chen et al. (2021) and Hall and Jones (2007).

Suppose individuals maximize their discounted lifetime utility $u(c) \cdot DLE(h)$ —the product of instantaneous utility function from annual consumption expenditure c and discounted life expectancy at birth depending on annual health expenditure h —subject to income constraint $m = c + h$. The optimality condition yields

$$\frac{\frac{DLE'(h) \cdot h}{DLE(h)}}{\frac{u'(c) \cdot c}{u(c)}} = \frac{h}{c} \quad (11)$$

The numerator on the left-hand side of equation (11) is the elasticity of discounted life expectancy that quantifies the effectiveness of health spending on longevity. This is estimated as

$$\frac{DLE'(h) \cdot h}{DLE(h)} = \frac{\pi(h)}{\pi(h) + \rho} \cdot \delta \quad (12)$$

where $\pi(h)$ is the mortality rate derived as the inverse of (undiscounted) life expectancy; ρ is assumed at 0.025; and $\delta \leq 0$ is the econometric estimate from regressing the logarithm of life expectancy on the logarithm of health expenditure.

Moreover, the denominator on the left-hand side of equation (11) is the elasticity of utility from consumption that measures the contribution of consumption to wellbeing. This is estimated as

$$\frac{u'(c) \cdot c}{u(c)} = \frac{c^{1-\omega}(1-\omega)}{c^{1-\omega}-1} \quad (13)$$

where c is consumption expenditure and ω is assumed at 1.01—consistent with Chetty (2006).

Equation (11) indicates that the optimality condition is achieved when the ratio of elasticities is equal to the ratio of expenditures. Note that equation (11) resembles the optimality condition

derived by Hall and Jones (2007). Rearranging the optimality condition (11) into macro-efficiency score yields

$$\frac{\frac{h}{c}}{\frac{DLE'(h) \cdot h}{DLE(h)} \cdot \frac{u(c)}{u'(c) \cdot c}} \lesseqgtr 1 \quad (14)$$

If an economy underspends/overspends on health, then the macro-efficiency score is less/greater than 1. To determine the optimal health expenditure h^* for a given level of consumption expenditures and elasticity of life expectancy, we recalculate equation (14) by setting the score equal to 1.0 and by applying the Generalized Reduced Gradient (GRG) Non-linear method to find the local optimum h^* . The macro-level analysis uses the data on life expectancy at birth, final consumption expenditure as a share of GDP, GDP per capita in purchasing power parity (PPP) dollars, and total health expenditure as a share of GDP. While other set of inputs and outputs can be used to calculate the optimality condition, this paper maintains the original framework and expands the analysis by covering 150 economies globally before and during the pandemic. Appendix Table A.2 has the complete description and sources of data.

4. Efficiency Scores

This section presents the evaluation of technical and allocative efficiency before and during the pandemic. The global sample comprises 180 economies at the maximum. The main sources of data are the World Bank, World Health Organization (WHO), and International Monetary Fund (IMF). Appendix Table A.2 has the complete list of variables, definition, and respective data sources.

4.1. Data Envelopment Analysis Score of Technical Efficiency

DEA measures the technical efficiency of an economy relative to others. The best performers are those economies located on the frontier having scores equal to 1.0. These economies are

“relative” and not “absolute” best performers. This means that relative best performers can still improve their performance that will cause the efficiency frontier to shift upwards. Low technical efficiency scores (i.e., below 1.0) could mean that either health expenditure is not fully utilized, or life expectancy is not fully realized. This paper evaluates the technical efficiency of total and government health expenditures per capita using the global sample of 178 economies. Based on the World Bank’s income classification, 30% of the sample is classified as lower-middle-income economies, another 30% as high-income, 28% upper-middle-income, and 12% low-income.⁵ Figures 4–5 presents technical efficiency scores using total health expenditure per capita as the input, while Figures 6–7 using government health expenditure per capita. All other estimations using private and current health expenditures per capita are in the Appendix.

4.1.1. Total Health Spending

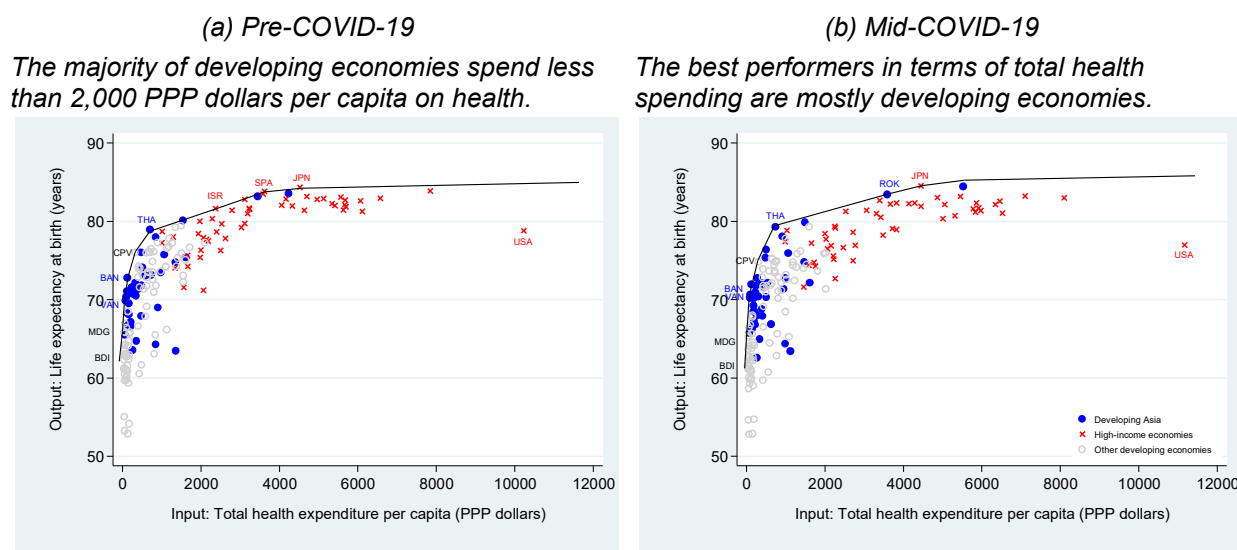
Three of the nine economies that defined the frontier before the pandemic were from developing Asia (Figure 4, panel [a]). These are Bangladesh, Thailand, and Vanuatu. It is worth noting that Japan, which spends 4,500 PPP dollars per capita (2017 real values) and has a life expectancy equal to 84 years old, is at the highest end of the frontier. Moreover, only eight economies defined the frontier during the pandemic (Figure 4, panel [b]). The ROK became one of the benchmark economies, aside from Bangladesh, Thailand, and Vanuatu. Japan is still at the highest end of the frontier. Israel and Spain fell short of the frontier.

The global average of total health expenditure per capita was approximately equal to 1,500 PPP dollars (2017 real values) before and during the pandemic. Of the 178 economies, 68% spent less than the global average, while the remaining 32% expended at least the global average. Moreover, the average life expectancy of economies spending less than the global average before and during the pandemic were 69 and 68 years old, respectively; and of those

⁵ The income classification of all economies is based on the World Bank 2023 update (calendar year = 2021).

economies expending at least the global average before and during the pandemic, average life expectancy were 80 and 79 years old, respectively. The economies that spend more on health have a higher life expectancy as compared to those who do not. This observation is not conclusive. The US is a good counterexample. It is the lowest point (red X marker) at the right side of the global frontier. Before the pandemic, the US spent 10,200 PPP dollars per capita on health but its life expectancy was 79 years old; while during the pandemic, it spent 11,200 PPP dollars per capita with a life expectancy equal to 77 years old when it could potentially be longer if the total health spending is efficient like Japan. Consequently, the application of DEA is a useful tool to assess how efficient an economy is (compared to the relative best performers) in spending its total health expenditure per capita.

Figure 4: Total health spending efficiency frontier



BAN = Bangladesh, BDI = Burundi, COVID-19 = coronavirus disease, CPV = Cabo Verde, ISR = Israel, JPN = Japan, MDG = Madagascar, ROK = Republic of Korea, SPA = Spain, THA = Thailand, VAN = Vanuatu.

Notes: The global sample covers 178 economies, including 41 developing Asian economies. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Total health expenditure per capita are 2017 real values.

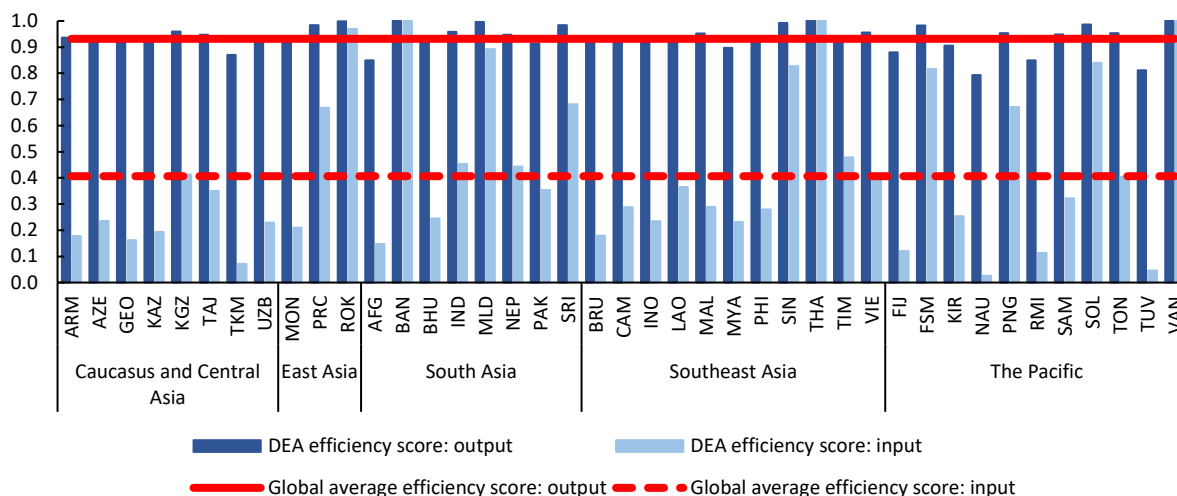
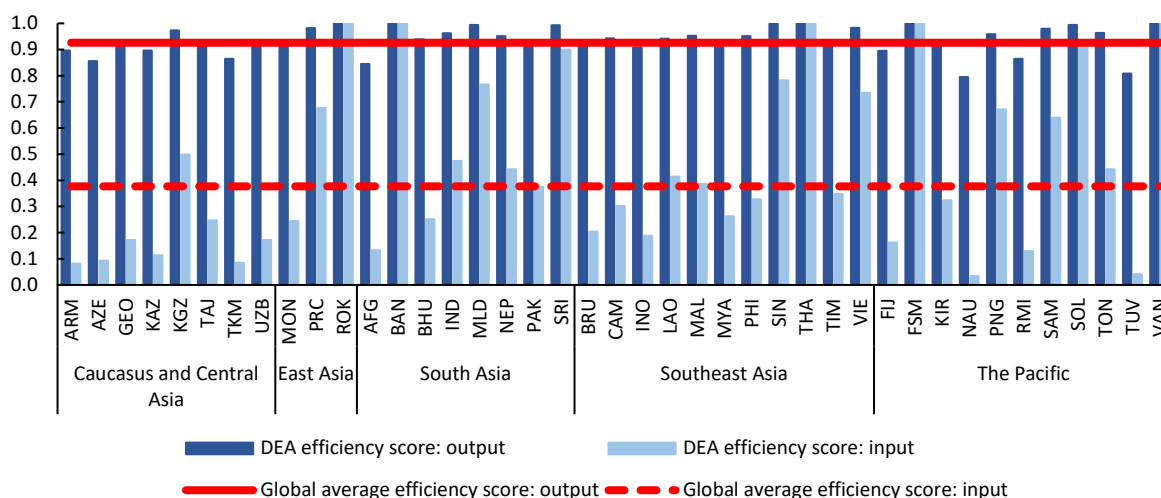
Source: Authors' calculations using data from the World Bank. World Development Indicators.
<https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

The output-oriented technical efficiency score is the extent to which life expectancy at birth (output) can be increased given the same level of total health expenditure per capita (input), while

the input-oriented technical efficiency score is the extent to which total health expenditure per capita (input) can be reduced to attain the same level of life expectancy at birth (output). Figure 5 presents the calculated efficiency scores that correspond to the one-input and one-output DEA model in Figure 4. Before the pandemic, Bangladesh, Thailand, and Vanuatu have technical efficiency scores of 1.0. After the pandemic, the ROK also gets a score of 1.0.

The global average score (red solid line) of output-oriented technical efficiency before the pandemic was 0.93. This means that the global economy was 7% ($= [1 - 0.93] \times 100\%$) short of the achievable life expectancy with efficient total health spending. Of the 41 developing Asian economies, 66% (or 27 economies) attained output-oriented efficiency scores that are equal to or higher than the global average. At the sub-regional level, East Asia had the highest score of 0.97, higher than the global average. South Asia and Southeast Asia attained 0.95, while Caucasus and Central Asia 0.93. The Pacific scored the lowest at 0.91. At the country level, Maldives and the ROK scored almost equal to 1.0, followed by Singapore at 0.99. Nauru achieved the lowest score at 0.79 among developing Asian economies.⁶ In other words, Nauru achieved 79% [is 21% short] of the potential life expectancy given the same level of total health expenditure.

⁶ Nigeria has the lowest score of 0.72 at the global level.

Figure 5: Total health spending efficiency scores using DEA*(a) Pre-COVID-19**East Asia has the highest output- and input-oriented technical efficiency scores—much higher than the global average score.**(b) Mid-COVID-19**East Asia remains to be the highest scorer, while Caucasus and Central Asia is the lowest.*

AFG = Afghanistan*, ARM = Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, BRU = Brunei Darussalam, CAM = Cambodia, COVID-19 = coronavirus disease, DEA = data envelopment analysis, FIJ = Fiji, FSM = Federated States of Micronesia, GEO = Georgia, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, MON = Mongolia, MYA = Myanmar**, NAU = Nauru, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, ROK = Republic of Korea, SAM = Samoa, SIN = Singapore, SOL = Solomon Islands, SRI = Sri Lanka, TAJ = Tajikistan, THA = Thailand, TIM = Timor-Leste, TKM = Turkmenistan, TON = Tonga, TUV = Tuvalu, UZB = Uzbekistan, VAN = Vanuatu, VIE = Viet Nam.

Notes: The global sample covers 178 economies, including 41 developing Asian economies. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Tables A.4 and A.5 list the output- and input-oriented technical efficiency scores of the global economy, respectively.

*ADB placed on hold its regular assistance in Afghanistan effective 15 August 2021. ADB Statement on Afghanistan | [Asian Development Bank](#) (published on 10 November 2021). Manila.

**ADB has placed on hold its assistance in Myanmar effective 1 February 2021. ADB Statement on Myanmar | [Asian Development Bank](#) (published on 10 March 2021). Manila.

Source: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

In addition, the global average score (red dashed line) of input-oriented technical efficiency before the pandemic was 0.41. That is, the global economy can decrease its total health expenditure per capita by 59% ($= [1 - 0.41] \times 100\%$) to achieve the same level of life expectancy at birth. Furthermore, 37% of (or 15 economies) developing Asian economies achieved input-oriented efficiency scores that are equal to or higher than global average score. At the sub-regional level, East Asia scored the highest at 0.62, higher than the global average. This is followed by South Asia at 0.53; and Southeast Asia, and the Pacific at 0.42. Caucasus and Central Asia scored 0.23. At the country level, the ROK scored 0.97 and Maldives 0.89. Nauru is the lowest scorer at 0.03 among developing Asian economies.⁷ This suggests that Nauru could have reduced its total health expenditure per capita by 97% to get the same level of life expectancy at birth.

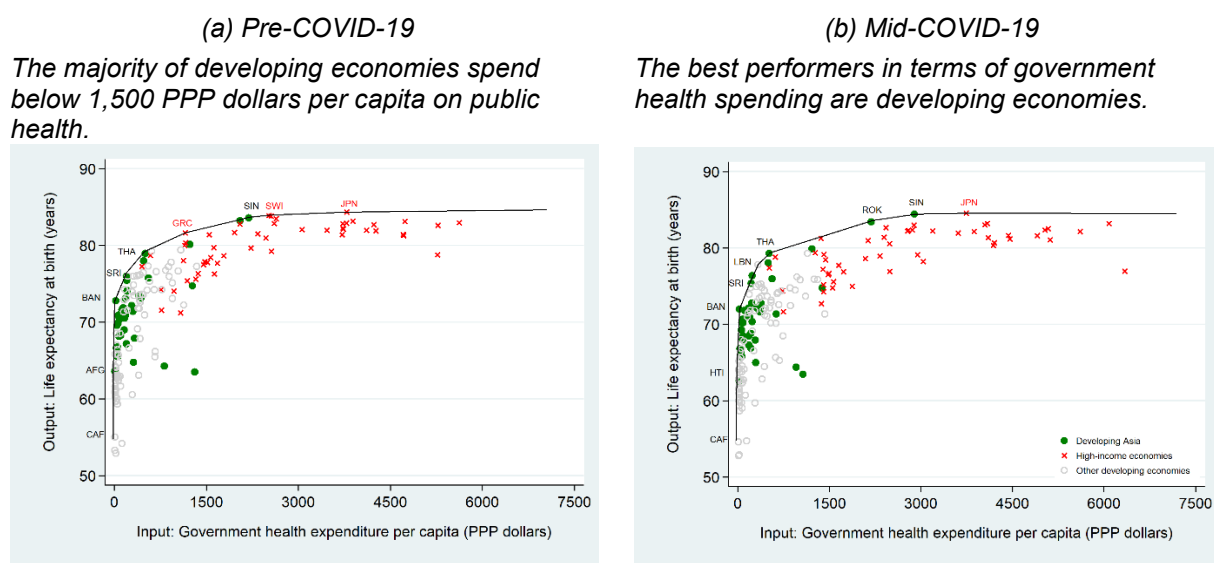
During the pandemic, the global average of output-oriented technical efficiency remained at 0.93. East Asia was still the highest scorer at 0.97, while Caucasus and Central Asia became the lowest scorer at 0.90. Additionally, the global average of input-oriented technical efficiency decreased by 0.03 from 0.41 before the pandemic. East Asia was still the highest scorer at 0.64. The Pacific improved a lot by 0.07, while Caucasus and Central Asia deteriorated and became the lowest scorer at 0.18.

⁷ Nauru remains to be the lowest scorer at the global level.

4.1.2. Government Health Spending

Five of the nine economies that defined the frontier before the pandemic were from developing Asia (Figure 6, panel [a]). These were Afghanistan⁸, Bangladesh, Singapore, Sri Lanka, and Thailand. Japan, which spent 3,800 PPP dollars per capita (2017 real values) on public health and had a life expectancy equal to 84 years old, was at the highest end of the frontier. Moreover, five benchmark economies were from developing Asia, but instead of Afghanistan, the ROK now defined the frontier (Figure 6, panel b). Japan is still at the highest end of the frontier. Greece and Switzerland fell short of the frontier.

Figure 6: Government health spending efficiency frontier



AFG = Afghanistan*, BAN = Bangladesh, CAF = Central African Republic, COVID-19 = coronavirus disease, GRC = Greece, HTI = Haiti, JPN = Japan, LBN = Lebanon, ROK = Republic of Korea, SIN = Singapore, SRI = Sri Lanka, SWI = Switzerland, THA = Thailand.

Notes: The global sample covers 178 economies, including 41 developing Asian economies. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Government health expenditure per capita are 2017 real values.

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Source: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

⁸ ADB placed on hold its regular assistance in Afghanistan effective 15 August 2021. ADB Statement on Afghanistan | [Asian Development Bank](#) (published on 10 November 2021). Manila.

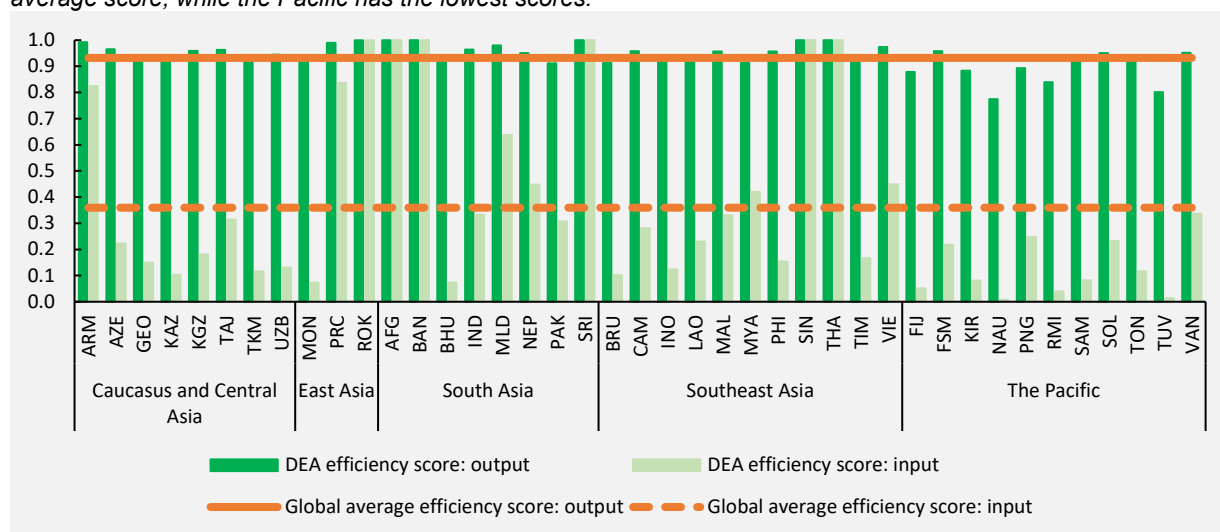
Recall that the output-oriented technical efficiency score is the extent to which life expectancy at birth (output) can be increased given the same level of government health expenditure per capita (input), while the input-oriented technical efficiency score is the extent to which government health expenditure per capita (input) can be reduced to attain the same level of life expectancy at birth (output). Figure 7 corresponds to the calculated scores using one-input and one-output DEA model in Figure 6. Before the pandemic, Afghanistan, Bangladesh, Singapore, Sri Lanka, and Thailand had efficiency scores of 1.0. After the pandemic, the efficiency score of Afghanistan deteriorated, but the ROK improved and achieved a score of 1.0.

The global average score (orange solid line) of output-oriented technical efficiency before the pandemic was 0.93. This means that the global economy was 7% ($= [1 - 0.93] \times 100\%$) short of the achievable life expectancy with efficient government health spending. Of the 41 developing Asian economies, 68% (or 28 economies) attained output-oriented efficiency scores that are equal to or higher than the global average. At the sub-regional level, East Asia and South Asia attained the highest score of 0.97, and Southeast Asia and Caucasus and Central Asia 0.95, which are higher than the global average. The Pacific scored the lowest at 0.89. At the country level, the ROK scored almost equal to 1.0, followed by Armenia and the PRC at 0.99. Nauru achieved the lowest score of 0.78 among developing Asian economies.⁹ In other words, Nauru achieved 78% [is 22% short] of the potential life expectancy given the same level of government health expenditure per capita.

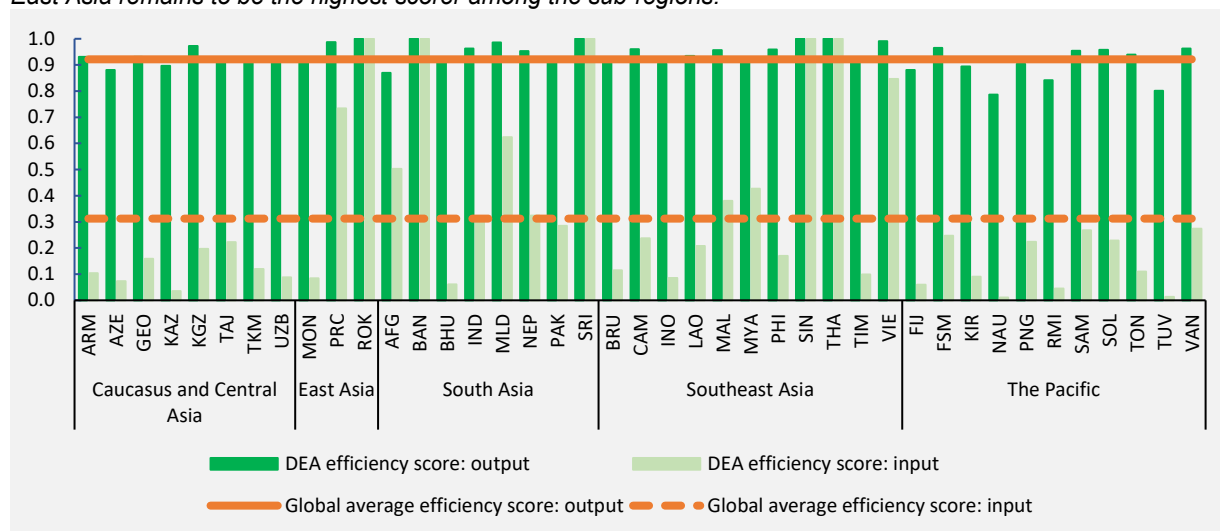
⁹ Lesotho has the lowest score of 0.73 at the global level.

Figure 7: Government health spending efficiency scores using DEA*(a) Pre-COVID-19*

East Asia has the highest output- and input-oriented technical efficiency scores—much higher than the global average score, while the Pacific has the lowest scores.

*(b) Mid-COVID-19*

East Asia remains to be the highest scorer among the sub-regions.



AFG = Afghanistan*, ARM = Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, BRU = Brunei Darussalam, CAM = Cambodia, COVID-19 = coronavirus disease, DEA = data envelopment analysis, FIJ = Fiji, FSM = Federated States of Micronesia, GEO = Georgia, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, KIR = Kiribati, LAO = Lao People's Democratic Republic, MAL = Malaysia, MLD = Maldives, MON = Mongolia, MYA = Myanmar**, NAU = Nauru, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PNG = Papua New Guinea, PRC = People's Republic of China, RMI = Marshall Islands, ROK = Republic of Korea, SAM = Samoa, SIN = Singapore, SOL = Solomon Islands, SRI = Sri Lanka, TAJ = Tajikistan, THA = Thailand, TIM = Timor-Leste, TKM = Turkmenistan, TON = Tonga, TUV = Tuvalu, UZB = Uzbekistan, VAN = Vanuatu, VIE = Viet Nam.

Notes: The global sample covers 178 economies, including 41 developing Asian economies. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Tables A.4 and A.5 list the output- and input-oriented technical efficiency scores of the global economy, respectively.

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Source: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

Moreover, the global average score (orange dashed line) of input-oriented technical efficiency was 0.36. That is, the global economy could decrease its government health expenditure per capita by 64% ($= [1 - 0.36] \times 100\%$) to achieve the same level of life expectancy at birth. Furthermore, 29% of (or 12) developing Asian economies achieve input-oriented efficiency scores that are equal to or higher than global average score. At the sub-regional level, East Asia scored the highest at 0.64, which is higher than the global average. This is followed by South Asia at 0.60, Southeast Asia at 0.39, and Caucasus and Central Asia at 0.26. The Pacific scored the lowest at 0.13. At the country level, the ROK scored almost equal to 1.0, followed by the PRC at 0.84. Tuvalu and Nauru scored the lowest at 0.01 and 0.007, respectively.¹⁰

During the pandemic, the global average of output-oriented technical efficiency was 0.92. East Asia was still the highest scorer at 0.97, while the Pacific was the lowest scorer at 0.90. In addition, the global average of input-oriented technical efficiency decreased by 0.05 from 0.36 before the pandemic. East Asia remained to be the highest scorer at 0.61. South Asia degraded by 0.09, and Caucasus and Central Asia deteriorated by 0.14 and became the lowest scorer at 0.12.

4.1.3. Sensitivity Analysis

In the preceding DEA, life expectancy at birth was used as the output. Comparing the findings using total health expenditure per capita (Figure 4) as the input versus government health expenditure per capita (Figure 6), Bangladesh, Japan, and Thailand consistently defined the frontier before and during the pandemic, and the ROK during the pandemic only.

In this paper, we perform sensitivity analysis by using four different outputs such as tuberculosis (TB) treatment success rate and survival rates of infant, neonatal, and under-five

¹⁰ Tuvalu and Nauru remain to be the lowest scorer at the global level.

children. Note that all survival rates are calculated using mortality rates. Appendix Table A.2 has the complete description and sources of data. All scores are available upon request.

It is worth noting that Bangladesh consistently defined the global frontier when technical efficiency is evaluated using government health expenditure per capita as the input, and infant and under-five children survival rates as the output. Bangladesh has been known as “positive deviant” for achieving better health outcomes despite economic poverty. It has significantly decreased infant, neonatal, and child mortality and reduced vaccine-preventable communicable diseases such as TB. The success of achieving better health outcomes and higher life expectancy in Bangladesh can be attributed to the advancement of women empowerment, access to primary education, application of evidence-based health research, and involvement of pluralistic health system that taps various stakeholders such as the government, private organizations, and international donors (Chowdhury et al. 2013, Ahmed et al. 2015, Lone and Hal 2022).

4.2. Macro-level Analysis Score of Allocative Efficiency

The tools for technical efficiency analysis are sensitive to the size and heterogeneity of the sample. DEA is sensitive to outliers and assumes homogenous economies, while SFA is sensitive to small sample size. On the other hand, the tool for allocative efficiency analysis is not sensitive to the size and heterogeneity of the sample. The macro-level analysis computes the scores of an economy independent of other economies. It determines whether an economy underspends (i.e., below 1.0) or overspends (i.e., higher than 1.0) on health. Figure 8 shows the estimated macro-level scores of developing Asia using total health expenditure (as a share of GDP) as the input. Appendix Table A.6 has the list of allocative efficiency scores. We also do several exercises in determining the macro-level scores using: (i) government health and government final consumption expenditures (columns 3–4 and 11–12); (ii) private health and private consumption expenditures (columns 1–2 and 9–10); and (iii) current health and final consumption expenditures (columns 7–8 and 15–16).

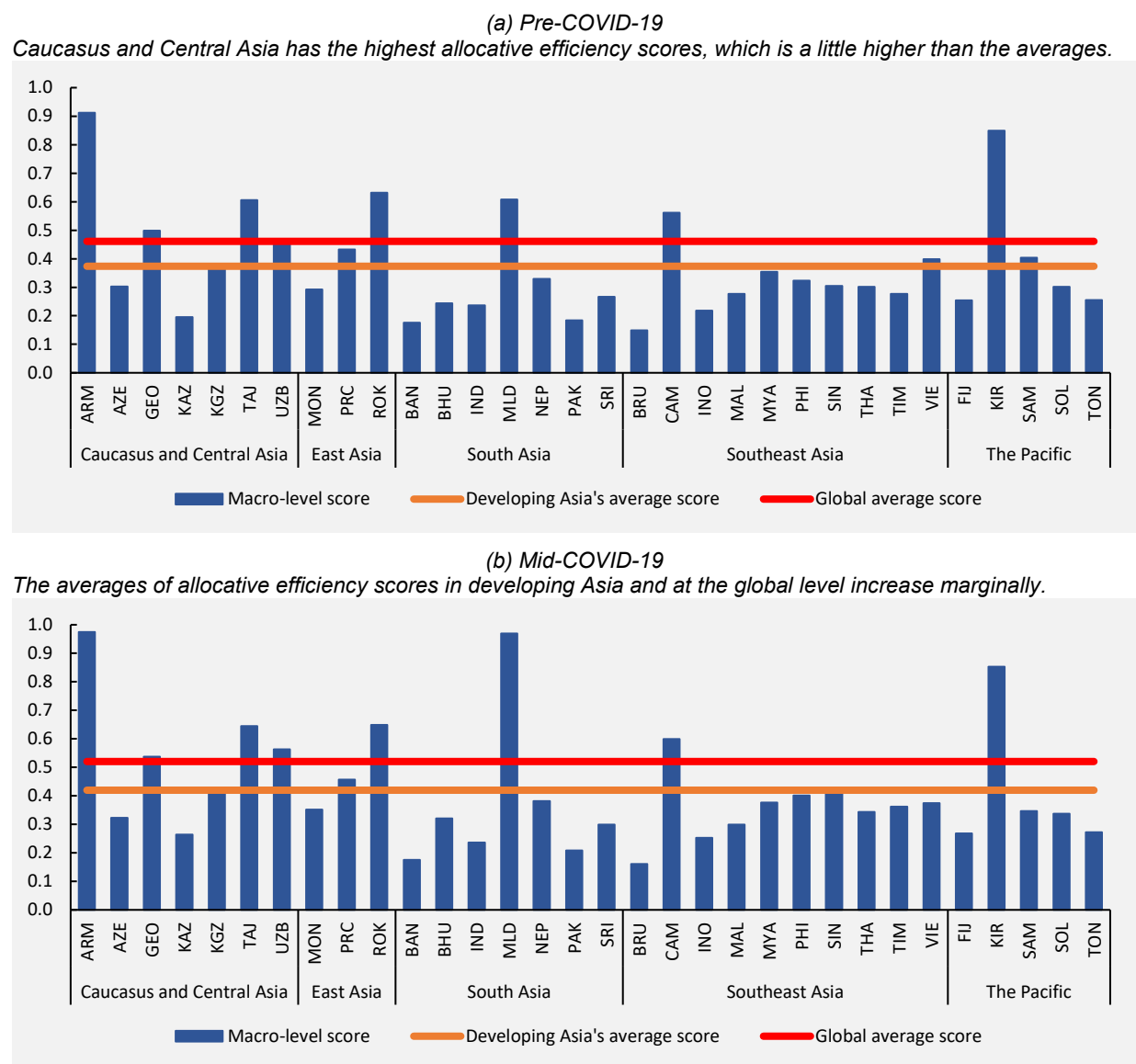
Before the pandemic, the average allocative efficiency score of the global economy (red line) was 0.46, while the average score of developing Asia (orange line) was 0.36. At the sub-regional level, Caucasus and Central Asia had an average score of 0.48, East Asia 0.45, and the Pacific 0.41. Southeast Asia and South Asia scored the lowest at 0.32 and 0.29, respectively. Note that the Pacific economies attained the lowest scores among developing Asian economies in the preceding technical efficiency analysis using DEA, while it achieved the highest score in the allocative efficiency analysis. This suggests that the Pacific, although far from optimal allocative efficiency, has room to enhance its technical efficiency—by improving life expectancy. The Pacific should address technical efficiency first before undertaking allocative efficiency. Once it becomes technically efficient, then perhaps the domestic private sector should partake in pursuing allocative efficiency. Recall that Appendix Figure A.1 shows that in the Pacific, government health expenditure per capita is eight times larger than private health expenditure per capita.

At the country level, Armenia and Kiribati had the highest allocative efficiency scores of 0.91 and 0.85, respectively. On the other hand, Bangladesh and Pakistan had low scores of 0.18; and Brunei Darussalam, which is categorized as high-income economy based on the World Bank's income classification, had the lowest score of 0.15. For reference, Japan had an allocative efficiency score of 0.87 and the US had 1.26—the only economy that overspent on health before the pandemic. Several studies have shown that the US spent more than the optimal (Cutler 2018, Holdsworth 2019). Based on the World Bank's World Development Indicator (2022), the US spent 17% of its GDP on current health expenditure in 2019. The estimated cost of waste in the US health care system is 25% of its current health expenditure (Shrank, Rogstad, and Parekh 2019).

During the pandemic, the averages of allocative efficiency scores at the global level and in developing Asia increased marginally by 0.06. At the sub-regional level, Caucasus and Central Asia led the highest score at 0.53, followed by East Asia at 0.49. The Pacific remained to be at 0.42. South Asia gained the score of 0.37, while Southeast Asia reached the lowest score of 0.36.

It is worth noting that among developing Asian economies, Maldives achieved the highest gain by 0.36, making it the highest scorer, together with Armenia, at 0.97. Brunei Darussalam remained to be the lowest scorer at 0.16. For reference, Japan scored 0.88. Only three economies overspent during the pandemic. These are Canada, Lebanon, and the US.

Figure 8: Total health spending efficiency scores using macro-level analysis



ARM = Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, BRU = Brunei Darussalam, CAM = Cambodia, COVID-19 = coronavirus disease, FIJ = Fiji, GEO = Georgia, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, KIR = Kiribati, MAL = Malaysia, MLD = Maldives, MON = Mongolia, MYA = Myanmar*, NEP = Nepal, PAK = Pakistan,

PHI = Philippines, PRC = People's Republic of China, ROK = Republic of Korea, SAM = Samoa, SIN = Singapore, SOL = Solomon Islands, SRI = Sri Lanka, TAJ = Tajikistan, THA = Thailand, TIM = Timor-Leste, TON = Tonga, UZB = Uzbekistan, VIE = Viet Nam .

Notes: While the macro-level analysis of allocative efficiency is country-specific, we cover 150 economies, including 32 developing Asian economies, in our estimations. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Table A.6 lists the allocative efficiency scores of the global economy.

*ADB has placed on hold its assistance in Myanmar effective 1 February 2021. ADB Statement on Myanmar | [Asian Development Bank](#) (published on 10 March 2021). Manila.

Source: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 31 May 2023).

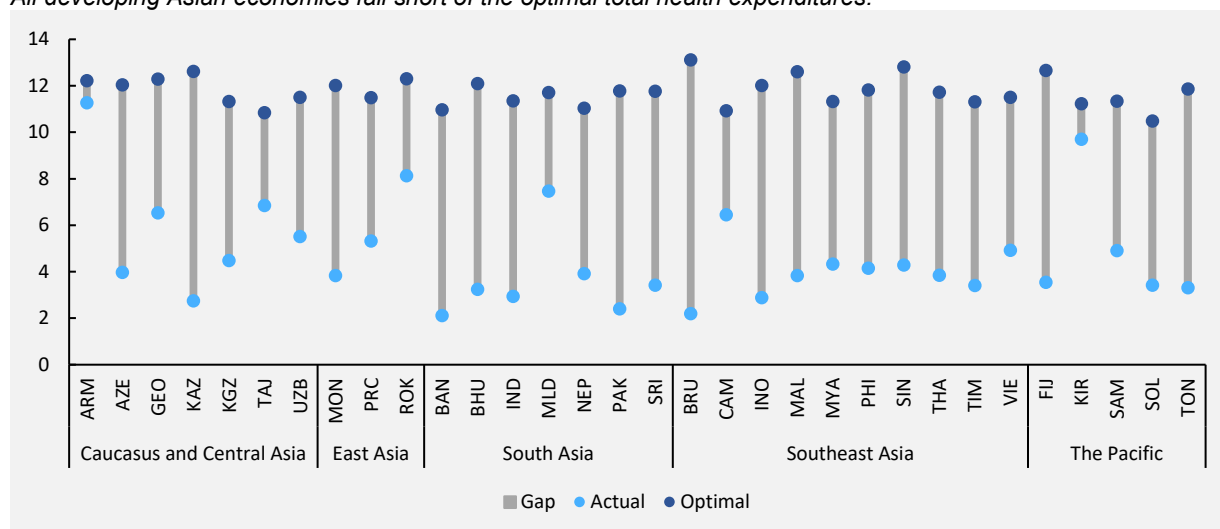
Figure 9 shows the gap between the actual and optimal total health expenditure as a share of GDP. Before and during the pandemic, the gap was largest in Brunei Darussalam (11%), followed by Kazakhstan (10%). Fiji is a relatively smaller economy compared to Indonesia and Malaysia, and yet all these three economies needed to up their total health expenditures by 9%. The Philippines and Thailand, which allot 4% of GDP on total health expenditure, needed to increase it to 12%. Moreover, the PRC and the ROK must increase their actual health expenditures by 6% and 4% of their respective GDP. On the other hand, the gap was lowest in Armenia and Kiribati. Maldives gained the lowest gap during the pandemic.

In a macro-level analysis, the current framework calculates the optimal total health expenditure as a share of GDP but does not compute the specific allocation from each sub-component of total health expenditure. This limits the analysis of allocative efficiency since the framework is novel. The next question on allocative efficiency is: what is the optimal mix/share of government and domestic private health expenditures to achieve welfare-maximizing health spending?

Figure 9: The gap between actual and optimal total health expenditures (% of gross domestic product) using macro-level analysis

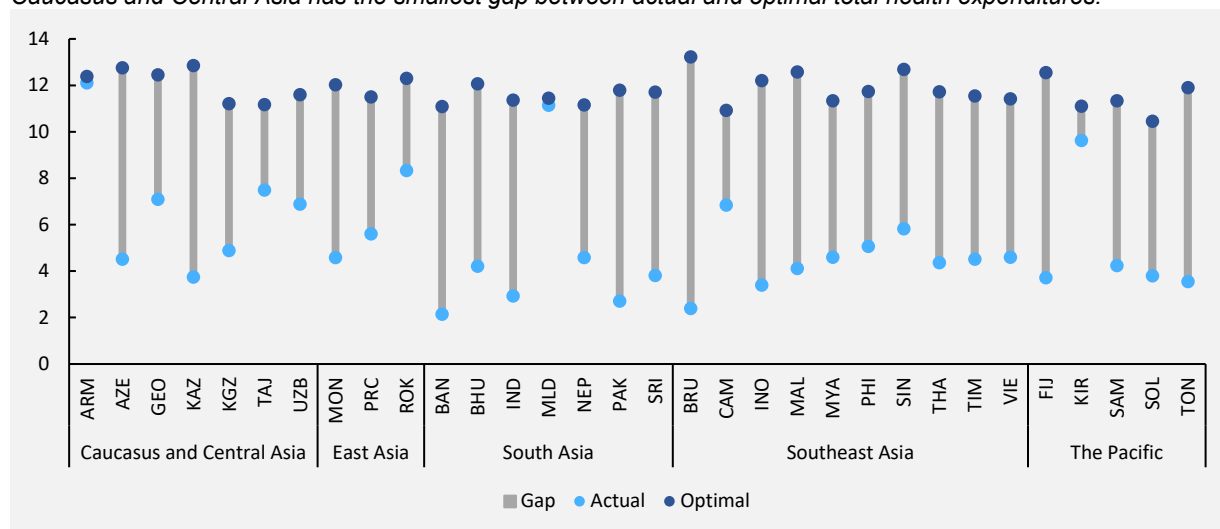
(a) Pre-COVID-19

All developing Asian economies fall short of the optimal total health expenditures.



(b) Mid-COVID-19

Caucasus and Central Asia has the smallest gap between actual and optimal total health expenditures.



ARM = Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, BRU = Brunei Darussalam, CAM = Cambodia, COVID-19 = coronavirus disease, FIJ = Fiji, GEO = Georgia, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, KIR = Kiribati, MAL = Malaysia, MLD = Maldives, MON = Mongolia, MYA = Myanmar*, NEP = Nepal, PAK = Pakistan, PHI = Philippines, PRC = People's Republic of China, ROK = Republic of Korea, SAM = Samoa, SIN = Singapore, SOL = Solomon Islands, SRI = Sri Lanka, TAJ = Tajikistan, THA = Thailand, TIM = Timor-Leste, TON = Tonga UZB = Uzbekistan, VIE = Viet Nam

Notes: While the macro-level analysis of allocative efficiency is country-specific, we cover 150 economies, including 32 developing Asian economies, in our estimations. Pre-COVID-19 and mid-COVID-19 scenarios use 2019 and 2020 data, respectively. Table A.7 lists the gap of the actual and optimal total health expenditures.

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5. Determinants of Health Spending Efficiency

Section 4.1 reveals that the majority of technically efficient economies are developing. This elicits the question about the factors influencing health spending efficiency.

The estimated input- and output-oriented efficiency scores using DEA range between 0 and 1. Ahmed et al. (2019) use Tobit regression analysis to account for the censoring of data. However, McDonald (2009) posits that DEA efficiency scores are fractional data, and Tobit regression, if applied, is an inconsistent estimator. In this paper, we estimate econometric model (15) using ordinary least squares (OLS) regression.

$$DEASc_i = \gamma_1 Gini_i + \gamma_2 UHC_i + \gamma_3 Popdens_i + \gamma_4 EducSh_i + \gamma_5 GovSh_i + \gamma_6 ForeignAssist_i + \gamma_7 Debt_i + \epsilon_i \quad (15)$$

where $DEASc$ are the estimated input- and output-oriented technical efficiency scores of (i) total health spending and (ii) government health spending using DEA. The control variables are Gini index, universal health coverage (UHC) service coverage index, population density, primary school enrollment rate, share of government in total health expenditure, foreign health assistance per capita, and central government's debt.¹¹ Appendix Table A.2 has the complete description and sources of data and Table A.8 contains the summary statistics.

We also account for the possibility of simultaneity bias—the error term of dependent variable (technical efficiency) is correlated with independent variables such as Gini index, foreign health assistance per capita, and UHC service coverage index. Using single-equation instrumental variables (IV) regressions, we use equations (16) to (19) in the first-stage regression

¹¹ Gini index measures income inequality, or how income distribution of individuals or households deviates from perfectly equal distribution. Additionally, UHC service coverage index (UHC SCI) quantifies the provision of and access to quality and essential health services. This index is based on tracer interventions including service capacity and access, infectious disease, non-communicable disease, reproductive, and child health (WHO 2022). Appendix Figure A.5 presents the formula to calculate UHC SCI. The list of indicators considered in the construction of UHC SCI is indicative and not exhaustive (WHO 2022). Appendix Figure A.6 illustrates the latest status of UHC service coverage in 2019.

and equation (15) in the second stage.¹² Appendix Tables A.9–A.12 have the results of IV estimations.

$$Gini_i = \tau_1 EducSh_i + \tau_k GDP_{i,t-k} + \zeta_i \quad (16)$$

$$ForeignAssist_i = \tau_1 Debt_i + \tau_k GDP_{i,t-k} + \zeta_i \quad (17)$$

$$UHC_i = \tau_1 EducSh_i + \tau_k GDP_{i,t-k} + \zeta_i \quad (18)$$

$$Y_i = \tau_1 EducSh_i + \tau_2 Debt_i + \tau_k GDP_{i,t-k} + \zeta_i \quad (19)$$

where $Y = \{Gini, ForeignAssist, UHC\}$; $t = 2019$ for pre-COVID scenario and $t = 2020$ for mid-COVID scenario; and $k = 0, 1, 2, 3, 4$

Table 1 presents the standardized coefficients of OLS regressions using equation (15). In pre- and mid-COVID-19 scenarios, we determine the factors affecting total health spending efficiency (columns 1–2, and 5–6) and government health spending efficiency (columns 3–4, and 7–8). Standardized coefficients are unitless coefficients and can be interpreted as “a change of one standard deviation in an independent variable is associated with a change of γ standard deviations of dependent variable”. These coefficients are commonly used to rank and compare the variables according to its absolute value. For example, γ_2 in column 1, UHC service coverage index has an absolute value of 0.4503. Its standardized coefficient has the largest magnitude and is significant at 1%. This means that before the pandemic, UHC service coverage index has the strongest effect on total health spending efficiency compared to all other explanatory variables in the model.

Using OLS regressions, we find that UHC service coverage and population density have the strongest effect on output- and input-oriented health spending efficiency, respectively, before and during the pandemic. Primary school enrolment rate and central government debt are positively associated with health spending efficiency as expected. The share of government in

¹² The estimation command in Stata is **ivregress (2sls)**.

total health expenditure is an important positive determinant of total health spending efficiency. On the other hand, Gini index is negatively associated with health spending efficiency.

Contrary to our expectation, foreign health assistance per capita is negatively associated with input-oriented government health spending efficiency. This means that the foreign transfers that flow into the national health systems are not used as efficiently as they should be. Aside from wasteful spending, other reasons of negative association of foreign health aid with spending efficiency could be attributed to: (i) aid misallocation, wherein the recipient economies miss the health targets or outcomes that need to be addressed; (ii) aid fragmentation (which usually emerges in poor and stable economies that receive large sums of foreign health assistance) costs time and money to supervise and manage health programs effectively, and causes duplication of the same (or equivalent) health projects; (iii) aid fungibility happens when the recipient economies decrease its government health expenditure and use foreign health aid to supplement the reduced amount, i.e., foreign health assistance serves as a substitute, not as a supplement; (iv) unpredictability of long-term support restrains the recipient economies to make sustainable commitments in health care delivery; (v) mutual unaccountability of donor and recipient economies (Martinez-Alvarez and Acharya 2012).

Table 1: Determinants of health spending efficiency

UHC service coverage and population density have the strongest effect on output- and input-oriented health spending efficiency, respectively.

Standard coefficients of:	Expected Sign	Pre-COVID-19				Mid-COVID-19			
		Total HSE		Government HSE		Total HSE		Government HSE	
		Output	Input	Output	Input	Output	Input	Output	Input
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini index (γ_1)	–	–0.1862** (0.0855)	–0.1537* (0.0924)	–0.1725** (0.0748)	–0.0541 (0.0855)	–0.0964 (0.0797)	–0.0891 (0.0880)	–0.01122* (0.0676)	–0.0226 (0.0837)
UHC service coverage index (γ_2)	+	0.4503*** (0.0979)	–0.0172 (0.1362)	0.6046*** (0.0704)	0.1417 (0.1083)	0.4211*** (0.1020)	–0.0604 (0.1332)	0.6302*** (0.0780)	0.0211 (0.1113)
Population density (γ_3)	+	0.0726 (0.0591)	0.2036** (0.1012)	0.0664 (0.0537)	0.2532*** (0.0943)	0.1105* (0.0617)	0.2310** (0.0986)	0.0939* (0.0624)	0.3230*** (0.1018)
Primary school enrolment (γ_4)	+	0.1288* (0.0884)	0.0683 (0.0907)	0.1321* (0.0707)	0.0016 (0.0678)	0.2004** (0.0921)	0.1458* (0.0834)	0.1702** (0.0765)	0.0353 (0.0688)
Share of government in total health expenditure (γ_5)	+	0.1755* (0.1018)	0.0810 (0.1202)			0.1725* (0.1160)	0.0804 (0.1264)		
Foreign health assistance per cap (γ_6)	+	–0.1143 (0.1634)	0.0424 (0.1597)	–0.0966 (0.1410)	–0.1283* (0.0666)	0.0077 (0.1564)	0.0958 (0.1650)	0.0365 (0.1321)	–0.1241* (0.0784)
Central government debt (γ_7)	+	0.1081* (0.0596)	0.2342** (0.1049)	0.0744 (0.0552)	0.1908* (0.1130)	0.1023* (0.0680)	0.1282 (0.1148)	0.0759 (0.0649)	0.1318 (0.1372)
Number of observations		106	106	106	106	99	99	99	99
R ²		0.4659	0.1393	0.5515	0.2049	0.3843	0.1179	0.5040	0.1785

COVID-19 = coronavirus disease, HSE = health spending efficiency, UHC = universal health coverage.

Notes: Robust standard errors are in parentheses. *** significant at 1%, ** at 5%, * at 10%, + at 15%.

Sources: Authors' calculations using data from the World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators#>. International Monetary Fund. Global Debt Database. https://www.imf.org/external/datamapper/CG_DEBT_GDP@GDD/SWE. CEIC Data Company. <https://www.ceicdata.com/en> (all accessed 31 May 2023).

6. Conclusion

This study aims to assess health spending efficiency in developing Asia. First, we estimate the technical efficiency scores of total and government health spending using DEA. Bangladesh and Thailand—two of the most efficient economies (i.e., with scores of 1.0)—define the global efficiency frontier both before and during the pandemic. Among the sub-regions of developing Asia, East Asia attains the highest output- and input-oriented technical efficiency scores. We also calculate the allocative efficiency scores of total health expenditure using the novel framework of macro-level analysis. Developing Asia spends below the optimal level of total health expenditure.

Second, we determine the sources of total and government health spending efficiency using OLS and IV regressions. We find that the negative determinant of health spending efficiency is income inequality, and the positive determinants are UHC service coverage, population density, primary school enrolment rate, and central government debt. The share of the government in total health expenditure is also a positive factor of total health spending efficiency. Counterintuitively, foreign health assistance per capita is negatively associated with health spending efficiency.

To conclude, developing Asia must improve both technical and allocative efficiency but technical efficiency should be the first priority. However, the optimal mix of government versus private financing of health expenditures cannot be answered by the macro-level framework of allocative efficiency, which does not differentiate between the two sources of health financing.

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Health Spending Efficiency in Developing Asia

This study analyzes health spending efficiency in developing Asia. The result shows universal health coverage service coverage index and population density as key determinants of health spending efficiency. While East Asia has the highest average technical efficiency score, Caucasus and Central Asia has the highest average allocative efficiency score. Overall, there is significant potential for improving both technical and allocative efficiency in health-care expenditures across developing Asia.

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