BMJ Global Health

Assessing the efficiency of countries in making progress towards universal health coverage: a data envelopment analysis of 172 countries

Emma Jordi,[1] Caitlin Pley,[2] Matthew Jowett,[3] Gerard Joseph Abou Jaoude ,[1] Hassan Haghparast-Bidgoli[1]

To cite: Jordi E, Pley C, Jowett M, *et al*. Assessing the efficiency of countries in making progress towards universal health coverage: a data envelopment analysis of 172 countries. *BMJ Global Health* 2020;**5**:e002992. doi:10.1136/bmjgh-2020-002992

Handling editor Lei Si

► Additional material is published online only. To view, please visit the journal online (http://dx.doi.org/10.1136/bmjgh-2020-002992).

Received 24 May 2020
Revised 6 September 2020
Accepted 28 September 2020

[1]Institute for Global Health, University College London, London, UK
[2]School of Clinical Medicine, University of Cambridge, Cambridge, UK
[3]Health Financing and Governance, World Health Organization, Geneva, Switzerland

Correspondence to
Dr Hassan Haghparast-Bidgoli; h.haghparast-bidgoli@ucl.ac.uk

ABSTRACT

Introduction Maximising efficiency of resources is critical to progressing towards universal health coverage (UHC) and the sustainable development goal (SDG) for health. This study estimates the technical efficiency of national health spending in progressing towards UHC, and the environmental factors associated with efficient UHC service provision.

Methods A two-stage efficiency analysis using Simar and Wilson's double bootstrap data envelopment analysis investigates how efficiently countries convert health spending into UHC outputs (measured by service coverage and financial risk protection) for 172 countries. We use World Bank and WHO data from 2015. Thereafter, the environmental factors associated with efficient progress towards UHC goals are identified.

Results The mean bias-corrected technical efficiency score across 172 countries is 85.7% (68.9% for low-income and 95.5% for high-income countries). High-achieving middle-income and low-income countries such as El Salvador, Colombia, Rwanda and Malawi demonstrate that peer-relative efficiency can be attained at all incomes. Governance capacity, income and education are significantly associated with efficiency. Sensitivity analysis suggests that results are robust to changes.

Conclusion We provide a 2015 baseline for cross-country UHC technical efficiency scores. If countries wish to improve their UHC outputs within existing budgets, they should identify their current efficiency and try to emulate more efficient peers. Policy-makers should focus on strengthening institutions and implementing known best practices to replicate efficient systems. Using resources more efficiently is likely to positively impact UHC coverage goals and health outcomes, and without addressing gaps in efficiency progress towards achieving the SDGs will be impeded.

Key questions

What is already known?

- High-income countries tend to be more efficient than low/middle-income countries in converting their health resources into health outcomes (increased life expectancy).
- Robust methodologies exist for comparing the technical efficiency of different countries but have not before been applied to a global set of countries to assess the efficiency with which health spending converts to universal health coverage (UHC) indicators.

What are the new findings?

- Although countries with higher incomes tend to be more efficient, some low-income and middle-income countries outperform higher income counterparts.
- The main drivers of efficiency in achieving UHC are governance, income and education.

What do the new findings imply?

- Efficiency is an important measure of progress on achieving UHC. This study serves as a benchmark on UHC efficiency prior to the introduction of the sustainabledevelopment goals (SDGs), enabling future work to draw comparisons of pre-SDG and post-SDG.
- Countries who perform relatively poorly (low efficiency) could learn from better performing peers and replicate efficient strategies to avoid wastage of resources while improving health outcomes.

BACKGROUND

Following the successes of the millennium development goals, the United Nations introduced 17 sustainable development goals (SDGs) to continue progress on global development. Within SDG 3 ('Ensure healthy lives and promote well-being for all at all ages'), target 3.8 aims to 'achieve universal health coverage (UHC), including financial risk protection, access to quality essential healthcare services and access to safe, effective, quality and affordable essential medicines and vaccines for all'.[1] UHC comprises three dimensions: covering more people, offering more services and increasing financial protection. Although no country will ever reach 100% of services for 100% of its people at no cost to the individual, progress is being made, although with each country following its unique path.[2] Performance management and efficiency are considered priorities for public health systems,[3] crucial to accelerate progress on health outcomes at times of slow economic growth and health budget limitations.[4]

WHO estimates that half of the world's population cannot access basic essential services, and in 2015, 12.7% of the global population experienced catastrophic health expenditures (out-of-pocket payments (OOP) greater than 10% of their household budgets).[5] There are stark global inequalities in both healthcare provision and health. Health and other inequalities leading to ill-health (eg, education, social behaviours, income and so on) exist both between and within countries, yet some countries have been able to achieve relatively better outcomes than peers with similar levels of income.[6] UHC aims to address within-country and cross-country inequalities in health by providing an underlying level of access to care for all individuals within a population. Other social inequalities ought to be addressed via other public and social interventions but are considered in this paper as factors associated with health status.

At this stage, it is unknown how efficiently different countries use their resources to progress towards UHC coverage goals. The WHO established performance measurement and efficiency as priorities for public health systems worldwide.[3] Given growing and ageing populations, fiscal constraints, competing development priorities, an expansion of healthcare options and providers, and an increased need for healthcare with a rising prevalence of non-communicable diseases, healthcare budgets are increasingly restricted and thus optimising health inputs to produce maximum health outcomes is a paramount management objective of public health systems. WHO has estimated that 20%–40% of health systems' resources are wasted,[2] thereby undermining service delivery. By reducing inefficiencies, welfare gains can be achieved in the absence of budget increases. This paper measures how efficiently countries convert existing resources into UHC, providing a benchmark of UHC performance in 2015, when the SDGs were introduced, and enabling cross-country comparisons going forward. Specifically, three questions are posed: (1) how efficient are different countries at converting healthcare inputs into UHC coverage goals? (2) what factors are associated with efficiency? and (3) what lessons can guide the efficient provision of UHC for countries going forward? This paper improves on the existing literature in four ways: first, it focuses on UHC service provision rather than health systems outcomes in general; second, it includes 172 countries in the analysis compared with smaller sample sizes found in other studies; third, it uses a complete service coverage index and finally, it applies a more robust and refined efficiency measurement technique.

METHODS

Data envelopment analysis (DEA)

DEA is a widely used linear programming technique to measure performance in healthcare because it offers a deterministic relationship between resource inputs and health outcomes, and can incorporate several inputs and outputs simultaneously.[4 7] DEA calculates a relative efficiency score for decision-making units (DMUs) based on an optimally weighted allocation for a set of inputs and outputs. DMUs, countries in this analysis, receive scores between 0 (least efficient) and 1 (most efficient) with the efficient DMUs forming a production frontier that envelopes others, and to which all inefficient DMUs are compared. DEA models define efficiency as the weighted sum of outputs to the weighted sum of inputs, comparing how well countries convert inputs into outputs. Inefficiency is then the ratio of actual to 'optimal' performance.[8]

DEA models can be input-oriented or output-oriented. The former minimises inputs for a constant set of outputs while the latter maximises outputs while holding inputs constant. This paper uses output-oriented DEA because changes to inputs are unlikely to take place in the short term in complex national health systems.[9] This approach is consistent with the existing literature, which has opted for output orientation in health system DEA[9–11] given that changes to inputs are unlikely to take place in the short-run and managers have little discretion over budget allocations.[12 13] Decentralised systems have far less control over how local units' budgets are allocated and cannot necessarily reallocate inputs.[14] Countries with large private healthcare markets or relying on donor aid also have little influence over how healthcare is organised. A description of the DEA algorithm can be found in online supplemental materials S1 and S2.

Secondary analysis

The two-stage DEA investigates the factors associated with the estimated efficiency scores. Simar-Wilson bootstrapping[15] is a two-stage DEA method that has been widely applied in analyses at the national, regional, hospital and ward levels.[12 16 17] The Simar-Wilson method adjusts the standard DEA score by the amount of bias caused by contextual factors. In the second stage, the bias-corrected efficiency scores are regressed in a truncated model against explanatory variables suspected of impacting the outputs, which corrects the estimates from serial correlation and measurement error of the technical efficiency scores.[18] Repeated samples are drawn with replacement, thus approximating the true sampling distribution of the DEA and subsequently estimating CIs not suffering from bias. In this study, 1000 bootstrap iterations are performed, thus allowing for a good approximation of 95% CIs.[15] The result measures technical efficiency, the ratio of actual output to maximum possible output or minimum possible input to actual input,[19] alongside the estimated bias-corrected efficiency scores.

Data sources

Cross-sectional data for health systems and environmental variables were obtained from the WHO Global Health Observatory and Global Health Expenditure Database,[20] and the World Bank's World Development Indicators for 193 countries.[21] Countries with missing data were excluded. Countries were grouped by income according to 2015 World Bank classifications. Patients and public were not involved in the research given that this was not relevant to the study.

Outputs

While progress has been made in compiling service coverage data, financial protection data remain sparse and outdated.[22] Typically, cross-country performance reviews include outputs such as life expectancy and mortality rates to reflect overall population health.[23–25] However, UHC coverage targets and indicators are more directly related to healthcare spending than health outcomes (eg, life expectancy and mortality) are, and therefore we opt to use UHC outputs as a more accurate reflection of the association between health spending and health outcomes.[17] To measure UHC attainment, two indicators from the UHC Monitoring Framework are used as output variables.[26]

UHC service coverage index

This WHO-produced index variable comprises 16 tracer indicators relating to reproductive, maternal and child health; non-communicable diseases; communicable diseases; and service capacity and access.[27] The index values for 2015 are available for all countries.

Proxy for financial risk protection

In the absence of complete data on financial risk protection, one minus OOPs (1–OOPs) as a proportion of current health expenditure (CHE) is used as a proxy for impoverishing spending. As data availability improves, catastrophic health expenditure (defined as OOPs exceeding a threshold of total household consumption[22]) should replace 1–OOPs/CHE as the output.

Combining these two outputs is important since they must be obtained simultaneously. High levels of service coverage is ineffectual if it leads to impoverishment; reduced OOP could reflect both good state-funded provision of care or low uptake of services due to cost barriers. To reflect this, the model is required to assign each output a weight greater than 0, forcing the model to include both.

Inputs

The input is CHE in 2015 int$. A 5-year average from 2011 to 2015 is used to reflect a lag in outputs and to smooth outliers and/or mismeasurement in the data. The paper considers CHE rather than government expenditure (as conducted previously by Jowett and colleagues[17]) because this includes other forms of health financing, including private pooled insurance and OOPs. If private input contributions were not included, service coverage would appear relatively more efficient for those countries with higher proportions of private payments.

Second-stage DEA: what explains variations in efficiency?

UHC efficiency can be explained by social, political, economic or environmental explanatory factors. Isolating those associated with UHC efficiency could highlight focus areas for policy-makers and control for inherent biases caused by factors outside of the health system. We expect variables such as income, governance, education and health system capital (number of beds and doctors) to be associated with efficiency. Detailed variable descriptions and their expected relationship with technical efficiency are presented in the online supplemental material S3.

Key statistics for inputs, outputs and explanatory variables

Descriptive statistics (included in online supplemental material S4) highlighted the unequal distribution of healthcare globally. Per capita health expenditure ranges from $23.4 in the Democratic Republic of the Congo (DRC) to $8181.5 in the USA. Even within low-income countries, Haiti spends seven times more ($159.8 per capita) than DRC. Similarly, 76% of expenditure on health in Yemen is out-of-pocket, compared with almost 0% in Kiribati. Average service coverage and government expenditure steadily increase across income groups. Electricity access more than doubles between low-income and lower-middle income countries. Education and governance appear to increase as income rises. Health worker density and number of beds increase steadily across income groups. Overall, country health profiles are heterogeneous, with trends favouring high-income countries.

Model specifications

The second-stage analysis included a Simar-Wilson bootstrap (Algorithm #2) to test bias-corrected variable returns-to-scale (VRS) efficiency scores against environmental variables to investigate which factors are associated with how efficiently countries provide UHC. The paper uses VRS rather than constant returns-to-scale because countries do not operate as optimal scales, whereby an increase in inputs produces a proportionate increase in output.[28] This analysis could aid policy-makers in determining which actions to take in order to reach UHC goals more efficiently, given the current level of national spending. Nine potential environmental variables were considered for inclusion in the double bootstrap regression. Spearman's rank correlation showed strong, but not severe correlation, with 0.7526 being the highest correlation value between education and governance. The main model includes eight environmental factors with data for all 172 countries, while the secondary model includes these eight plus the Gini Index, which had data available for 145 countries. Service coverage prioritises equity-seeking countries and inequality might impact efficiency. Therefore, the secondary model captures the effect of within-country inequalities.

Sensitivity analysis

To assess the robustness of the findings, given that DEA can produce sensitive results, an in-depth sensitivity analysis was performed. The following adjustments were made to determine the robustness of results:

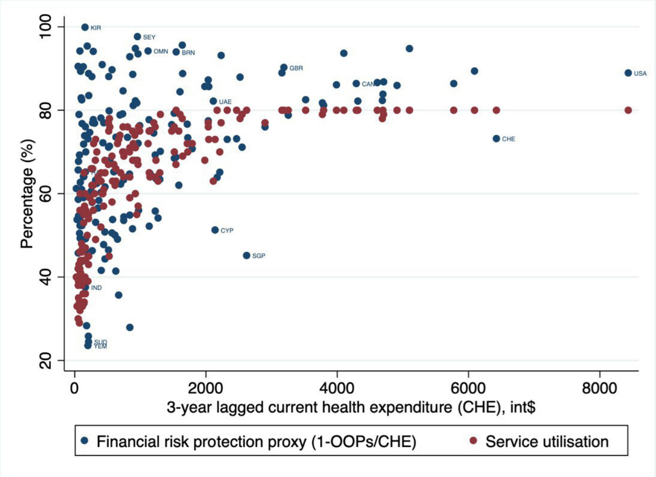


Figure 1 UHC indicators by current health expenditure. CHE, current health expenditure; OOP, out-of-pocket payment; UHC, universal health coverage.

1. The financial protection proxy, 1–OOPs/CHE, was substituted with domestic general government expenditure (GGHE-D)/CHE, which is a similar and alternative proxy for financial protection, but without considering private pooled insurance.
2. 3-year lag for CHE were used in place of the 5-year lagged average to test the sensitivity of the time lag.
3. Outlying countries were removed one at a time, since deterministic models like DEA do not allow for random noise and are particularly sensitive to outliers.
4. Tobit regression as an alternative methodology was used as second stage in place of Simar-Wilson.

RESULTS

There is an exponential relationship globally between health expenditure and both UHC indicators (figure 1). Initially, small increases in health expenditure yield large changes in service coverage and financial protection. Yet, as levels of health expenditure rise, the marginal improvement to UHC outputs diminishes. There are decreasing marginal returns because the most cost-effective programmes are typically implemented first. From figure 1, it appears that there is little additional benefit when spending more than $2000 per capita. However, this is partly because the service coverage indicator omits the benefits of secondary-level and tertiary-level spending outside of the 16 tracer indicators, which reflect primary care coverage. Under $2000 per capita, large health gains are associated with marginal additional expenditure.

Technical efficiency of converting health spending into UHC outputs

Table 1 indicates that high-income countries can improve their efficiency by up to 5%. By comparison, low-income countries can produce 31% more UHC outputs under full efficiency. These findings suggest high-income countries on average produce UHC outputs more efficiently than other income groups after correcting for bias. Top performers by income group are Switzerland, Austria and Belgium (high income), Colombia, Brazil and Peru (upper-middle income), El Salvador, Samoa and Vietnam (lower-middle income) and Malawi, Zimbabwe and Rwanda (low income).

Associations of technical efficiency

Results from the Simar-Wilson bias-corrected regression identify three variables that were statistically significantly associated with a country's technical efficiency (table 2). These are: (a) Gross Domestic Product (GDP) per capita, (b) governance capacity and (c) education. Higher income, better governance and more years of schooling within a country are associated with greater technical efficiency in converting health spending to UHC goals. Governance has the strongest relationship with efficiency and a one unit increase in governance could lead to a 0.06-unit improvement in UHC service goals, keeping health expenditure constant.

When including the Gini index for a secondary model with a subset of 145 countries, findings suggest that inequality is significantly positively associated with technical efficiency but results in governance becoming insignificant. Countries with more inequality tend to more efficiently provide UHC. This is the opposite of what is to be expected and therefore this result should be interpreted cautiously.

Sensitivity analysis of efficiency scores

The sensitivity analysis demonstrated that the results of this study are largely robust (further details in online supplemental material S5). Substituting the financial protection proxy to GGHE-D/CHE had an average effect of 0.1% across all countries' bias-corrected efficiency scores and resulted in income becoming insignificant and electricity significant. Removing efficient and outlier DMUs did not substantially impact results, with three countries moving more than 5% on average and none changing more than 7%. Education, GDP per capita, governance and electricity were significant when using a Tobit regression instead of a Simar-Wilson bootstrap.

DISCUSSION

Associations of efficiency

This paper estimates how efficiently total health expenditure per capita is converted into UHC service goals for 172 countries in 2015 and provides a pre-SDG baseline for future analyses. We address a gap in the literature on UHC efficiency by using most recent UHC data and applying a more robust methodology, specifically DEA with a double bootstrap truncated regression analysis, to more countries than in previous studies. Given large heterogeneity across countries, comparisons are made within peer groups.

The main study findings suggest that although high-income countries tend to outperform lower income countries, some countries such as Colombia, El Salvador

Table 1 Summary of bias-corrected Shepherd efficiency scores by income group (full results in online supplemental material S4)

	Income group				
	Low income	**Lower-middle income**	**Upper-middle income**	**High income**	**All countries**
Number of countries	26	46	49	51	172
Mean	0.69	0.82	0.88	0.95	0.86
SD	(0.11)	(0.10)	(0.07)	(0.05)	(0.12)
Minimum	0.50	0.55	0.73	0.80	0.50
Maximum	0.86	0.96	0.97	1	1
Top 3	Malawi, Rwanda, Zimbabwe	El Salvador, Samoa, Vietnam	Angola, Bosnia and Herzegovina, Albania	Latvia, Lithuania, United Arab Emirates	Malawi, Rwanda, Zimbabwe
Bottom 3	Mali, Sierra Leone, Afghanistan	Mauritania, Sudan, Yemen	Colombia, Peru, Brazil	Switzerland, Austria, Belgium	Switzerland, Austria, Belgium

and Malawi outperform their income group peers. This implies that for a given level of resources and spending, peers could increase their performance and increase their outcomes against UHC indicators. Peers should emulate best practice approaches that these outperforming countries have taken, to the extent that they are compatible in the national and local context. Simar-Wilson bootstrap results suggest that, in the main model, GDP per capita (income), governance capacity and education have a statistically significant relationship with how efficiently a country can convert spending into UHC service goals.

The mean efficiency scores by income group after bias-correction were 95% (SD 0.05), 88% (SD 0.07), 82% (SD 0.10) and 69% (SD 0.11) for high, upper-middle, lower-middle and low-income countries respectively. The lowest score was 49.9% for Mali. Figure 2 shows the distribution of bias-corrected efficiency scores within income groups.

There are opportunities to improve efficiency

Many countries, particularly low or middle income, can drastically improve the efficiency with which they provide UHC. Specific policy changes should be investigated further for contextual, evidence-based and implementable advice for decision-makers at national levels. We show that there are three ways to improve efficiency. The first is reducing healthcare expenditure, holding all else constant. Most countries showed decreasing returns to scale in the DEA. Covering more people becomes increasingly costly since hard-to-reach individuals are covered last, at greater cost. Countries with worse health outcomes are likely to experience the effects of diminishing marginal returns, where initial returns to investment are high and decrease as the investment increases. As countries spending little spend more, the gap in spending will close and efficiency gains from low spending will be less pronounced. To improve efficiency at already high levels of expenditure, countries require an even greater focus on efficiency to improve health outcomes. This said, even at higher marginal costs, governments should continue to prioritise health spending given the direct relationship with health and quality of life associated therewith. Three common drivers in countries' UHC trajectories include: political reforms in favour of UHC; income growth and increased health spending; and increased pooled spending over OOP.[29] Thus, increasing health spending will help countries progress towards achieving UHC. Highly privatised health systems are also considered more inefficient than public ones, and therefore countries should try to reduce fragmentation and move towards unitary publicly financed health systems to improve efficiency.[30]

More services can be provided for the same expenditure by reallocating and diversifying resources towards most cost-effective programmes, thereby covering more essential services. For example, Chad and DRC have low scores for access to modern family planning methods and tuberculosis treatment coverage. Increasing service coverage from the lowest score to the highest is associated with 21 years of additional life.[27] One way to reduce costs

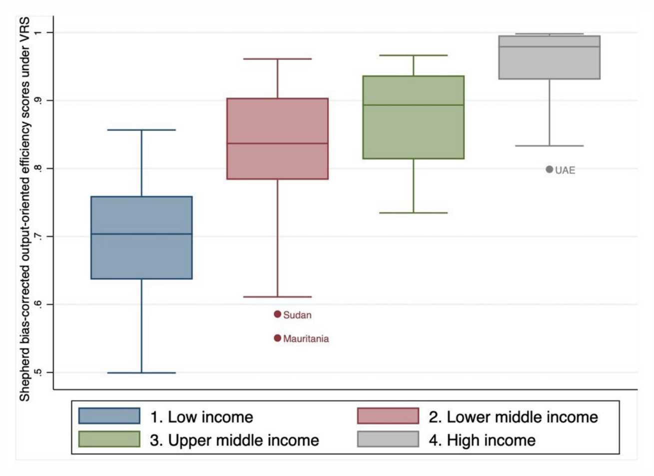


Figure 2 Distribution of VRS bias-corrected efficiency scores by income group. VRS, variable returns-to-scale.

Table 2 Associations of Simar-Wilson bias-corrected efficiency scores

	Main model			**Second model (incl. Gini Index)**		
Variable	Coefficient **(SE)**	Lower	Upper	Coefficient **(SE)**	Lower	Upper
GDP	2.77×10^{-6}* (1.13×10^{-6})	8.1×10^{-7}	5.2×10^{-6}	5.6×10^{-6}*** (1.74×10^{-6})	2.02×10^{-6}	8.88×10^{-6}
Education	0.0249*** (0.00661)	0.0115	0.0370	0.0222*** (0.00645)	0.00868	0.0339
Electricity	0.000445 (0.000407)	−0.000351	0.00124	0.000762 (0.000407)	−0.000028	0.00158
Log population	−0.00439 (0.00478)	−0.0137	0.00488	−0.00866 (0.0050907)	−0.0186	0.000890
Population density	0.0000206 (0.0000342)	−0.000031	0.00124	0.0000339 (0.0000434)	−0.000040	0.000136
Urban popoulation	−0.000320 (.0005721)	−0.00144	0.000802	−0.000932 (0.000598)	−0.00209	0.000221
Governance	0.0573** (0.0187)	0.0193	0.0929	0.0258 (0.0199)	−0.0141	0.0632
Beds	−0.000134 (0.000540)	−0.00123	0.000929	−0.000247 (0.000528)	−0.00123	0.000869
Health worker	0.000437 (0.000869)	−0.000733	0.002624	0.000519 (0.000855)	−0.000582	0.00275
Income inequality (Gini)	–	–	–	0.00386** (0.00126)	0.00144	0.00661
Constant	0.547*** (0.0760)	0.399	0.707	0.434 (0.0866)	0.256	0.598

*p<0.05, **p<0.01, ***p<0.001.
n=172 for main model, n=145 for secondary model.
GDP, Gross Domestic Product.

and provide more services would be a shift to primary and preventative healthcare, which often requires improving step-down facilities and procedures for referral.[30]

Good governance matters

Good local governance plays a significant role in achieving UHC service goals efficiently, according to our results. The role of strong governance mechanisms in allocating health resources most efficiently and effectively, thereby improving health coverage and status, is recognised in the context of maternal and child health, a key dimension of UHC.[31] More broadly, one leading theory on the causative processes leading to economic growth and development suggests that development is reliant on institutions.[32] We have shown that governance (defined as institutional strength, institutional memory and political commitment) are key to achieving UHC coverage goals. Political engagement, ideally at the highest levels of government, is also a likely prerequisite to achieving UHC efficiency improvements.

In addition to developing local governance, policymakers can seek guidance from global governance mechanisms and non-state actors which also play a critical role in local delivery of health programmes, through collective action and developing norms and standards.[33] Good governance practices supported by national and supranational health actors, including governments, large donors and international organisations, should be locally tailored to suit national interests before being implemented but can provide pragmatic solutions to delivering care equitably, effectively and cost efficiently.

Efficiency gains can compound

While producing more outputs for the same level of inputs is itself valuable, efficiency gains may support requests for budget reallocation towards healthcare if ministries can prove to national treasuries or aid donors that they are attaining a high return on investment. Funds may migrate towards programmes or countries providing efficient UHC services.

Does income matter?

Income is significant in both the main model and the secondary (includes Gini Index). Both models demonstrate clear trends in UHC provision efficiency by income group. Lower efficiency scores are predominantly seen among lower income nations, many of which suffer from political, economic and regional instability. Yet, lower income does not eliminate the possibility for countries to perform efficiently. El Salvador, Samoa and Vietnam (lower-middle-income) have scores higher than some high-income countries (for example Estonia, Bahrain and Slovakia) and Malawi (low-income) performs better than several upper-middle-income countries. Prior to bias correction, several low-income countries are equally as efficient as high-income countries, suggesting that income group does not eliminate the ability to provide UHC efficiently.[24] Income likely aids efficiency, but UHC efficiency can be attained at any income level with the right supporting factors in place.

Our findings that income (GDP per capita), education and governance are related to how efficiently countries convert health spending into UHC are aligned with findings from similar studies (although these look at healthcare not UHC).[34 35] Standard cross-country efficiency studies are frequently criticised in that measures of health (typically life expectancy and mortality) are highly influenced by factors widely outside the health system.[36] Our approach better withstands this criticism since it is measuring the efficiency of the health system's ability to produce UHC service goals (a direct relationship) and not good health generally (an indirect relationship).

We explored the relationship between UHC efficiency and good health more generally, which is the ultimate goal of UHC provision. UHC is important for achieving good health outcomes[37] but the relationship between how efficiently UHC is provided and good health has not been investigated. Figure 3 shows a strong linear relationship between bias-corrected technical efficiency scores and health-adjusted life expectancy (HALE) in the following year. Since the latest data on HALE are from 2016, and historical UHC data are not available, a time lag could not be incorporated and a full regression analysis should be performed when the data become available.

DEA methodology has intrinsic limitations. It is deterministic, relying heavily on the data selected; it is only as good as the data that inform it and cannot perform where data are absent, nor can it produce useful estimates if the underlying data are inaccurate. Additionally, DEA provides a relative measure of each unit to 'perfectly efficient' peers scoring one, and so including or excluding certain peers could influence the relative performance and results. The methodology assumes a homogeneous production function, which is unrealistic, as not all countries have access to the same human capital and technology. Efforts should be made to complete datasets for countries with missing health systems data to avoid the need for a financial protection proxy. The choice of variables used for the second-stage analysis was largely dependent on data availability. Many of these limitations have been addressed through sensitivity analysis. The conclusions drawn from the findings remained largely consistent despite adjustments to the models. Further studies could investigate the optimal combination of primary to secondary/tertiary care maximum efficiency or the effects of UHC efficiency on HALE. These questions require more nuanced healthcare data.

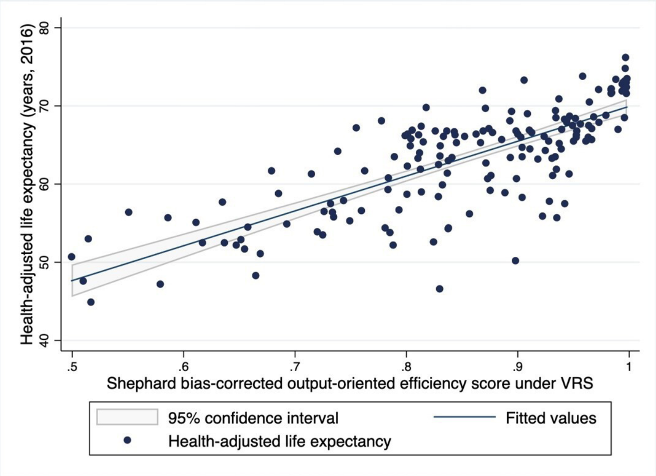


Figure 3 Relationship between bias-corrected technical efficiency scores and HALE in the following year. HALE, health-adjusted life expectancy; VRS, variable returns-to-scale.

CONCLUSION

These findings provide a benchmark for the efficiency that countries convert expenditure to UHC, offering a useful comparison for post-SDG studies assessing progress towards UHC attainment. This study fills a literature gap in UHC-specific efficiency analysis and benefits from its wide country coverage and its robust methodology. The findings suggest that although high-income countries tend to outperform lower income countries, some countries such as Colombia, El Salvador and Malawi outperform their income group peers. Peer countries could emulate some of the best practice approaches these countries have taken, to the extent that they are compatible in the national and local context. Better governance, improved education, higher GDP per capita and Gini Index are significantly associated with how efficiently countries convert total health expenditure into UHC. Health outputs, such as UHC efficiency, may be better indicators than health outcomes to guide national policy development for health system strengthening, as health outputs have a more direct relationship with national health spending. Efficiently producing UHC is likely to positively impact health outcomes, and without addressing gaps in efficiency, progress towards achieving the SDGs will be impeded.

Contributors HH-B and EJ conceptualised the study. EJ collected and collated the data, carried out the analysis and wrote the first draft of the paper. HH-B, CP, MJ and GJAJ contributed to the interpretation of the results and contributed to the final written version of the paper. All authors approved the final version of the manuscript.

Funding The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Competing interests None declared.

Patient consent for publication Not required.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are publicly available from the WHO Global Health Observatory database, and may be shared directly upon request.

ORCID iD

Gerard Joseph Abou Jaoude http://orcid.org/0000-0001-6022-3036

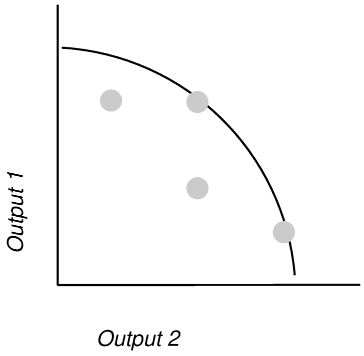
REFERENCES

1 United Nations. *Transforming our world: the 2030 agenda for sustainable development*. , 2015: 16301, 1–35.
2 Evans DB, Etienne C. Health systems financing and the path to universal coverage. *Bull World Health Organ* 2010;88:402.
3 Daher M. Overview of the world health report 2000 health systems: improving performance. *J Med Liban* 2001;49:1–215.
4 Cantor VJM, Poh KL. Integrated analysis of healthcare efficiency: a systematic review. *J Med Syst* 2018;42:1–23.
5 World Bank Group, World Health Organization. Global monitoring report on financial protection in health 2019, 2019. Available: https://data.worldbank.org/indicator/SH.UHC.OOPC.10.ZS [Accessed 06 Jan 2020].
6 Balabanova D, Mills A, Conteh L, *et al*. Good health at low cost 25 years on: lessons for the future of health systems strengthening. *Lancet* 2013;381:2118–33.
7 Hussey PS, De Vries H, Romley J, *et al*. A systematic review of health care efficiency measures: health care efficiency. *Health Serv Res* 2009;44:784–805.
8 Moreno-Serra R, Anaya-Montes M, Smith PC. Potential determinants of health system efficiency: evidence from Latin America and the Caribbean. *PLoS One* 2019;14:e0216620:1–21.
9 See KF, Yen SH. Does happiness matter to health system efficiency? A performance analysis. *Health Econ Rev* 2018;8:33.
10 Ahmed S, Hasan MZ, MacLennan M, *et al*. Measuring the efficiency of health systems in Asia: a data envelopment analysis. *BMJ Open* 2019;9:e022155.
11 Pérez-Cárceles MC, Gómez-Gallego JC, Gómez-Gallego M. Environmental factors affecting European and Central Asian health-systems' bias-corrected efficiency. *Appl Econ* 2018;50:3432–40.
12 Achoki T, Hovels A, Masiye F, *et al*. Technical and scale efficiency in the delivery of child health services in Zambia: results from data envelopment analysis. *BMJ Open* 2017;7:e012321.
13 Mujasi PN, Asbu EZ, Puig-Junoy J. How efficient are referral hospitals in Uganda? A data envelopment analysis and tobit regression approach. *BMC Health Serv Res* 2016;16:230.
14 Yang C-C. Measuring health indicators and allocating health resources: a DEA-based approach. *Health Care Manag Sci* 2017;20:365–78.
15 Simar L, Wilson PW. Estimation and inference in two-stage, semi-parametric models of production processes. *J Econom* 2007;136:31–64.
16 Bobo FT, Woldie M, Wordofa MA, *et al*. Technical efficiency of public health centers in three districts in Ethiopia: two-stage data envelopment analysis. *BMC Res Notes* 2018;11:465.
17 Jowett M, Cylus J. Spending targets for health: no magic number. health financing working paper No. 1.Work Pap, 2016. Available: http://apps.who.int/iris/handle/10665/250048
18 Lépine A, Vassall A, Chandrashekar S. The determinants of technical efficiency of a large scale HIV prevention project: application of the DEA double bootstrap using panel data from the Indian Avahan. *Cost Eff Resour Alloc* 2015;13:1–11.
19 Hollingsworth B. The measurement of efficiency and productivity of health care delivery. *Health Econ* 2008;17:1107–28.
20 WHO. *Global health expenditure data*, 2019.
21 World Bank Group. *World development indicators*, 2019.
22 Wagstaff A, Flores G, Hsu J, *et al*. Progress on catastrophic health spending in 133 countries: a retrospective observational study. *Lancet Glob Health* 2018;6:e169–79.
23 Hadad S, Hadad Y, Simon-Tuval T. Determinants of healthcare system's efficiency in OECD countries. *Eur J Health Econ* 2013;14:253–65.
24 Retzlaff-Roberts D, Chang CF, Rubin RM. Technical efficiency in the use of health care resources: a comparison of OECD countries. *Health Policy* 2004;69:55–72.
25 Evans DB, Tandon A, Murray CJL, *et al*. Using data envelopment analysis to address the challenges of comparing health system efficiency. *Glob Policy* 2017;3:60–8.
26 World Bank Group, World Health Organisation. *Tracking Universal Health Coverage : 2017 Global Monitoring Report*. Washington DC, Geneva, 2017.
27 Hogan DR, Stevens GA, Hosseinpoor AR, *et al*. Monitoring universal health coverage within the sustainable development goals: development and baseline data for an index of essential health services. *Lancet Glob Health* 2018;6:e152–68.
28 Jacobs R, Smith PC, Street A. *Measuring efficiency in health care: Analytic techniques and health policy*. Cambridge University Press, 2006.
29 Savedoff WD, de Ferranti D, Smith AL, *et al*. Political and economic aspects of the transition to universal health coverage. *Lancet* 2012;380:924–32.
30 Stuckler D, Feigl AB, Basu S, *et al*. *The political economy of universal health coverage. background paper for the global Symposium on health systems research*, 2010.
31 Wehrmeister FC, da Silva ICM, Barros AJD, *et al*. Is governance, gross domestic product, inequality, population size or country surface area associated with coverage and equity of health interventions? ecological analyses of cross-sectional surveys from 80 countries. *BMJ Glob Health* 2017;2:e000437.
32 Acemoglu D, Johnson S, Robinson JA. Institutions as a fundamental cause of long-run growth. *Handb Econ growth* 2005;1:385–472.
33 Fryatt R, Bennett S, Soucat A. Health sector governance: should we be investing more? *BMJ Glob Health* 2017;2:e000343.
34 Afonso A, St. Aubyn M. Assessing health efficiency across countries with a two-step and bootstrap analysis. *Appl Econ Lett* 2011;18:1427–30.
35 Ravangard R, Hatam N, Teimourizad A, *et al*. Factors affecting the technical efficiency of health systems: a case study of economic cooperation organization (Eco) countries (2004-10). *Int J Health Policy Manag* 2014;3:63–9.
36 Cylus J, Papanicolas I, Smith PC. *Health system efficiency how to make measurement matter for policy and management*. London, 2016.
37 Moreno-Serra R, Smith PC. *Broader health coverage is good for the nation's health : evidence from country level panel data*, 2015: 101–24.

Supplementary Materials

S1. DEA Methodology in Detail

Data Envelopment Analysis (DEA) uses linear programming techniques to assess how efficiently multiple inputs are able to produce multiple outputs, either by maximising outputs for a given set of inputs (output-oriented) or minimising inputs to achieve a certain output (input-oriented). DEA is a type of ‘frontier analysis’ meaning that the model output is a rank ordering of decision making units (DMUs) compared to a frontier of fully efficient DMUs. Thus, inefficient DMUs are enveloped by top performing units in multidimensional space (which depends on the number of inputs and outputs used). In this case, there is one input and two outputs and so the production frontier is a surface in three-dimensional space. Inefficiency is then measured as the distance from the DMU to the frontier; this is the amount by which the DMU can improve its outputs while maintaining the same level of inputs. The idea is thus to maximise the ratio of the sum of the outputs to the sum of the inputs, each weighted such that the DMU is “cast in the best light possible”; in other words, no alternative weights could improve the performance of the DMU.[28]



The optimisation problem is thus as follows:

$$\max\left(\frac{\sum_{s=1}^{S} u_s y_{s0}}{\sum_{m=1}^{M} v_m x_{m0}}\right)$$

subject to:

$$\frac{\sum_{s=1}^{S} u_s y_{si}}{\sum_{m=1}^{M} v_m x_{mi}} \leq 1 \qquad \text{i=1,…, I}$$

where:

y_{s0} is the quantity of output s for DMU$_0$;

u_s is the weight of output s and $u_s > 0$;

x_{m0} is the quantity of output m for DMU$_0$;

v_m is the weight of output s and $v_m > 0$;

for s=1,…S and m=1,…,M

In the case of output maximisation, the sum of inputs must be held constant and thus the denominator is unity. The optimisation problem is therefore rewritten as follows:

$$\text{Max } \theta_0 = \sum_{s=1}^{S} u_s y_{s0}$$

subject to:

$$\sum_{m=1}^{M} v_m x_{m0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_m x_{mi} \leq 0 \;\; i = 1, \ldots n$$

$$u_r, v_i \geq 0$$

These constraints ensure a denominator equal to one, that the sum of all outputs cannot exceed the sum of all inputs and that the weights for each variable must be strictly positive. This ensures that all inputs and outputs are present in the solution.

As a set of linear equations, this is written as follows:

$$Max_{v,u}\ \theta_0 = uy_i$$

subject to:

$$vx_i = 1$$

$$-vX + uY \leq 0$$

$$u, v \geq 0$$

Where x_i and y_i represent input and output vectors for all I DMUs; u, v are row vectors for input and output weights, and X, Y are input and output matrices representing data for all I DMUs. θ is a scalar and $\theta \leq 1$, representing level of efficiency with one being fully efficient compared to peers. The minimisation problem for input-orientation is analogous to this.

S2. Truncated regression bootstrap methodology[36]

Algorithm #2 consists of the following steps (adapted from Badunenko and Tauchmann[31]):

1. Compute $\widehat{\theta_\iota}$ $f$or all DMUs i = 1, . . . , N using DEA.

2. Use those M (with M < N) DMUs, for which $\hat{\theta}_i$ > 1 holds, in a truncated regression (left-truncation at 1) of $\hat{\theta}_i$ on **z**$_i$ to obtain coefficient estimates $\hat{\beta}$ and an estimate for variance parameter $\hat{\sigma}$ by maximum likelihood.

3. Loop over the following steps 3.1–3.4 *B*$_1$ times, in order to obtain a set of *B*$_1$ bootstrap estimates $\widehat{\theta_\iota^b}$. for each DMU i=1, …, N, with b = 1, . . . , B$_1$.

3.1 For each DMU i = 1, . . . , N, draw an artificial error $\widetilde{\varepsilon_\iota}$ from the truncated N(0, $\hat{\sigma}$) distribution with left-truncation at 1− **z**$_i\hat{\beta}$.

3.2 Calculate artificial efficiency scores $\widetilde{\theta_\iota}$ as **z**$_i\hat{\beta}$ + $\widetilde{\varepsilon_\iota}$ for each DMU i = 1, . . . , M.

3.3 Generate $i = 1, \ldots, N$ artificial DMUs with input quantities $\widetilde{x_\iota}$ = x_i and output quantities $\widetilde{y_\iota}$ = $(\frac{\widehat{\theta_\iota}}{\widetilde{\theta_\iota}})y_i$.

3.4 Use the N artificial DMUs, generated in step 3.3, as reference set in a DEA that yields $\widehat{\theta_\iota^b}$ for each original DMU i = 1, …, M.

4. For each DMU **I** = 1 , … , N, calculate a bias corrected efficiency score $\widehat{\theta_\iota^{bc}}$ as $\widehat{\theta_\iota}$ – $(\frac{1}{B_1}\sum_{b=1}^{B_1}\widehat{\theta_\iota^b} - \widehat{\theta_\iota})$.

Calculate confidence intervals and standard errors for $\hat{\beta}$and $\hat{\sigma}$ from the bootstrap distributions of $\hat{\beta}^b$ and $\hat{\sigma}^b$.

5. Run a truncated regression (left-truncation at 1) of $\widehat{\theta_\iota^{bc}}$ on **z**$_i$ to obtain coefficient estimates $\hat{\hat{\beta}}^b$and $\hat{\hat{\sigma}}^b$ by maximum likelihood.

6. Loop over the following steps 6.1 – 6.3 *B*$_2$times, in order to obtain a set of *B*$_2$ bootstrap estimates $\hat{\hat{\beta}}^b$and $\hat{\hat{\sigma}}^b$, with b = 1, …, B$_2$.

6.1 For each DMU i = 1 N draw an artificial error $\tilde{\tilde{\varepsilon}}$ from the truncated N(0 $\hat{\hat{\sigma}}^b$)

Figure 1: Truncated Bootstrap Regression, Algorithm #2

S3. Variable descriptions

1. *Gross Domestic Product (GDP) per capita*

Income plays an important role in the ability of countries to provide services across the 16 health indicators. Income is correlated to other development indicators (poverty and education for example) but is frequently used with these indicators in regression models. Average GDP per capita is used to indicate average income levels for countries and therefore their ability to pay for health services provision.

2. *Governance*

The World Bank's World Governance Indicators (WGI) consists of six measures on national governance: Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption. National governance is represented by the mean of these six variables, which are scored from -2.5 to 2.5. The variables are strongly correlated and therefore cannot be included in the regression model individually.

3. *Education*

The average number of years of schooling that a child of school entrance age can expect to receive is used as a measure of population level education.[9] Better education, particularly girl's education, is closely linked to improved overall population health, and also contributes to increased availability of trained health workers and better management in the health sector.[37]

4. *Inequality*

The Gini Coefficient is a unit-free measure of income inequality reflecting national difference in distribution of income. A score of 0 represents perfect equality and 1 represents perfect inequality.

5. *Electricity*

The percentage of the population with access to electricity is used for this indicator. Only a third of sub-Saharan African hospitals have reliable electricity provision, which particularly affect utilization of essential health care services.[38] Electricity access acts as a quality indicator.

6. Population size

Population data are widely available and extracted from GHO for all countries. To reduce the spread of data, the natural logarithm is taken for all countries.

7. Urbanisation

The percentage of total population living in urban areas is used as the measure for this indicator. Service provision in urban populations is more cost-effective since they are easier to reach than rural populations.

8. Population Density

Population density (the number of people per square kilometer) could affect how efficiently care is delivered in facilities, as well as the distribution of medical supplies or demand for services. A higher population density could affect efficiency through economies of scale, as shown by a number of health system efficiency studies.[39,40]

9. Inverse of OOP

The inverse of OOP is an alternative measure of financial protection and represents the amount not paid for by users at the point of care. This incorporates donor expenditure, non-governmental organisations and financial aid not considered in general government health expenditure output.

10. Physician density

Medical staff density (number of medical doctors per 100,000 people) is commonly used as the labour input in efficiency studies and was used in this study as a proxy for capacity of health systems to provide essential outpatients and primary health services. Ideally, a health worker density indicator that includes other staff such as community health workers, nurses and midwives, in addition to doctors, would be a better proxy but there is lack of comparable data across countries for other staff.

11. Beds

The number of hospital beds (per 100,000), which is commonly used as capital input in efficiency studies, was used as a proxy for the capacity of health systems to provide essential inpatient services.

Descriptive Statistics of DEA and explanatory variables

Variable Name	**Low income**					**Lower middle income**					**Upper middle income**					**High income**				
	n	***Mean***	***SD***	***Min***	***Max***	***n***	***Mean***	***SD***	***Min***	***Max***	***n***	***Mean***	***SD***	***Min***	***Max***	***n***	***Mean***	***SD***	***Min***	***Max***
CHE per capita	26	87.7	36.5	23.4	159.8	46	245.7	141.6	70.3	650.9	49	773.8	325.7	163.1	1998.0	51	2845	1570	793.8	8181
1-OOPs/CHE	26	62.1	13.3	36.1	90.5	46	61.8	21.1	23.6	99.9	49	68.1	15.5	27.9	95.6	51	79.9	11.0	45.2	97.7
Service coverage	26	40.0	6.44	29	55	46	55.4	10.6	33	77	49	67.2	8.4	36	78	51	76.3	4.8	63	80
GDP per capita	26	1577	583	583	2828	46	5191	2472	1762	11349	49	14436	5116	6819	31543	51	40678	20052	16361	12086
Gini coefficient	25	41.3	6.64	32.8	56.2	44	38.9	7.2	25	57.1	39	40.0	10.1	16.6	63	38	32.9	5.3	25.4	47.7
Education	26	9.6	1.85	5.3	12.6	46	11.6	1.9	6.2	15	49	13.7	1.6	9.2	17.4	51	16.2	2.0	12.7	23.3
Electricity	26	31.6	21.3	7.3	87.21	46	76.7	23.4	22.2	100	49	94.3	12.7	42	100	51	99.9	0.5	96.8	100
Governance	26	-0.8	0.4	-1.6	-0.04	46	-0.5	0.5	-1.9	0.6	49	-0.3	0.6	-1.8	0.9	51	1.0	0.6	-0.4	1.9
Urban population	26	33.1	12.2	12.1	58.53	46	43.7	17.1	13.0	77.4	49	64.0	16.6	18.5	91.5	51	76.8	16.4	25	100
Log of population	26	9.5	1.11	6.9	11.54	46	9.0	2.2	4.7	14.10	49	9.0	2.0	4.7	14.1	51	8.7	1.8	4.5	12.7
Population density	26	126.7	134.8	7.3	471.4	46	129.8	187.3	1.9	1238.4	49	123.6	224.1	3.0	1394.7	51	354.7	1110.6	3.1	7806.8
Health worker density	26	1.2	1.2	0.2	6.0	46	8.1	8.7	0.5	32.4	49	18.6	14.2	1.0	74.8	51	34.4	30.7	9.3	239.2
Beds	26	7.1	4.8	1	22	46	21.3	18.4	4	88	49	32.3	21.9	8	110	51	43.4	24.0	12	134

Notes: *SC= Service coverage; GGHE-D/CHE = Domestic General Government Health Expenditure as a % of current health expenditure; CHE = current health expenditure (lagged and averaged)*

S4. Full DEA scores for the main model

Rank	Country	Income group	DEA Score	Bias	Shephard BC Score
1	Switzerland	4	1,00	0,00	1,00
2	Austria	4	1,00	0,00	1,00
3	Belgium	4	1,00	0,00	1,00
4	Australia	4	1,00	0,00	1,00
5	Sweden	4	1,00	0,00	1,00
6	Norway	4	1,00	0,00	1,00
7	Iceland	4	1,00	0,00	1,00
8	Singapore	4	1,00	0,00	1,00
9	Denmark	4	1,00	0,00	1,00
10	Canada	4	1,00	0,00	1,00
11	Japan	4	1,00	0,00	1,00
12	Italy	4	1,00	0,00	1,00
13	USA	4	1,00	0,00	1,00
14	Luxembourg	4	1,00	0,00	1,00
15	Israel	4	1,00	0,01	0,99
16	Portugal	4	1,00	0,01	0,99
17	South Korea	4	1,00	0,01	0,99
18	New Zealand	4	1,00	0,01	0,99
19	UK	4	1,00	0,01	0,99
20	Barbados	4	1,00	0,01	0,99
21	France	4	1,00	0,01	0,99
22	Finland	4	0,99	0,00	0,98
23	Malta	4	0,99	0,00	0,98
24	Germany	4	0,99	0,00	0,98
25	Netherlands	4	1,00	0,02	0,98
26	Uruguay	4	0,99	0,01	0,98
27	Brunei Darussalam	4	1,00	0,03	0,97
28	Ireland	4	0,97	0,00	0,97
29	Qatar	4	0,98	0,01	0,97
30	Colombia	3	0,99	0,03	0,97
31	Seychelles	4	1,00	0,03	0,97
32	Slovenia	4	0,97	0,01	0,96
33	Peru	3	1,00	0,04	0,96
34	Brazil	3	0,97	0,01	0,96
35	Oman	4	0,98	0,02	0,96
36	El Salvador	2	1,00	0,04	0,96
37	Spain	4	0,96	0,00	0,96
38	Mexico	3	0,97	0,01	0,96
39	Thailand	3	1,00	0,05	0,95
40	Kuwait	4	0,96	0,01	0,95
41	Samoa	2	0,98	0,03	0,95
42	Argentina	3	0,96	0,01	0,95
43	Algeria	3	0,97	0,02	0,95
44	Viet Nam	2	1,00	0,05	0,95
45	China	3	0,97	0,03	0,95
46	Fiji	3	0,97	0,02	0,95
47	Estonia	4	0,95	0,01	0,94
48	Ecuador	3	0,95	0,01	0,94
49	Botswana	3	0,97	0,02	0,94

50	Slovakia	4	0,95	0,01	0,94
51	Antigua and Barbuda	4	0,96	0,02	0,94
52	Uzbekistan	2	0,98	0,04	0,94
53	Dominican Republic	3	0,96	0,02	0,94
54	Costa Rica	3	0,95	0,01	0,94
55	South Africa	3	0,96	0,03	0,94
56	Solomon Islands	2	0,99	0,05	0,93
57	Poland	4	0,94	0,01	0,93
58	Panama	3	0,95	0,01	0,93
59	Tajikistan	2	1,00	0,07	0,93
60	Micronesia	2	0,96	0,03	0,93
61	Trinidad and Tobago	4	0,94	0,01	0,93
62	Kiribati	2	1,00	0,07	0,93
63	Belarus	3	0,94	0,01	0,93
64	Tonga	2	0,96	0,04	0,92
65	Venezuela	3	0,95	0,02	0,92
66	Namibia	3	0,95	0,02	0,92
67	Suriname	3	0,94	0,02	0,92
68	Romania	3	0,93	0,02	0,91
69	Cabo Verde	2	0,94	0,02	0,91
70	Nicaragua	2	0,94	0,03	0,91
71	Croatia	4	0,93	0,02	0,91
72	Cyprus	4	0,91	0,01	0,91
73	Guyana	3	0,94	0,04	0,90
74	Grenada	3	0,92	0,02	0,90
75	Kyrgyzstan	2	0,95	0,04	0,90
76	Turkey	3	0,93	0,03	0,90
77	Jordan	3	0,94	0,04	0,90
78	Sao Tome and Principe	2	0,93	0,03	0,90
79	Bahamas	4	0,91	0,01	0,90
80	Eswatini	2	0,92	0,03	0,90
81	Czechia	4	0,91	0,02	0,89
82	Kazakhstan	3	0,91	0,01	0,89
83	Bahrain	4	0,90	0,01	0,89
84	Kenya	2	0,94	0,06	0,89
85	Saudi Arabia	4	0,90	0,01	0,89
86	Malaysia	3	0,89	0,01	0,88
87	Egypt	2	0,90	0,02	0,88
88	Timor-Leste	2	0,94	0,06	0,88
89	North Macedonia	3	0,89	0,02	0,87
90	Bhutan	2	0,90	0,03	0,87
91	Vanuatu	2	1,00	0,13	0,87
92	Chile	4	0,88	0,01	0,87
93	Hungary	4	0,88	0,01	0,87
94	Greece	4	0,87	0,01	0,87
95	Paraguay	3	0,88	0,02	0,87
96	Saint Lucia	3	0,88	0,02	0,86
97	Malawi	1	0,94	0,08	0,86
98	Lebanon	3	0,86	0,01	0,85
99	Morocco	2	0,87	0,03	0,84
100	Armenia	2	0,85	0,01	0,84
101	UAE	4	0,85	0,01	0,84

102	St Vincent and the Grenadines	3	0,86	0,02	0,84
103	Zimbabwe	1	0,88	0,04	0,84
104	Bolivia	2	0,87	0,03	0,84
105	Zambia	2	0,88	0,05	0,84
106	Turkmenistan	3	0,85	0,02	0,84
107	Honduras	2	0,87	0,04	0,84
108	Lithuania	4	0,84	0,01	0,83
109	Rwanda	1	0,89	0,06	0,83
110	Georgia	3	0,85	0,01	0,83
111	Moldova	2	0,86	0,03	0,83
112	Lesotho	2	0,86	0,03	0,83
113	Belize	3	0,86	0,03	0,83
114	Myanmar	2	0,87	0,04	0,83
115	Sri Lanka	2	0,86	0,03	0,83
116	Burundi	1	0,97	0,14	0,82
117	Maldives	3	0,84	0,02	0,82
118	Iran	3	0,82	0,01	0,82
119	Iraq	3	0,84	0,03	0,81
120	Serbia	3	0,82	0,01	0,81
121	Mongolia	2	0,84	0,03	0,81
122	Ukraine	2	0,84	0,03	0,81
123	Tunisia	2	0,83	0,02	0,81
124	Bangladesh	2	0,88	0,07	0,81
125	Jamaica	3	0,83	0,03	0,81
126	Mauritius	3	0,81	0,01	0,80
127	Azerbaijan	3	0,81	0,01	0,80
128	Bulgaria	3	0,81	0,01	0,80
129	Libya	3	0,84	0,04	0,80
130	Gabon	3	0,82	0,02	0,80
131	Latvia	4	0,81	0,01	0,80
132	Congo	2	0,84	0,04	0,79
133	Russia	3	0,80	0,01	0,79
134	Mozambique	1	1,00	0,21	0,79
135	Equatorial Guinea	3	0,81	0,02	0,79
136	Cambodia	2	0,83	0,05	0,78
137	India	2	0,83	0,05	0,78
138	Gambia	1	0,87	0,09	0,78
139	Albania	3	0,79	0,02	0,78
140	Philippines	2	0,80	0,04	0,76
141	Comoros	1	0,82	0,06	0,76
142	Bosnia and Herzegovina	3	0,77	0,02	0,75
143	Haiti	1	0,82	0,07	0,75
144	Laos Republic	2	0,79	0,04	0,74
145	Guatemala	2	0,76	0,02	0,74
146	Angola	3	0,77	0,04	0,73
147	Ghana	2	0,77	0,04	0,73
148	Ethiopia	1	0,85	0,12	0,73
149	Tanzania	1	0,82	0,09	0,73
150	Benin	1	0,80	0,08	0,72
151	Togo	1	0,78	0,06	0,72
152	Nepal	1	0,76	0,05	0,71
153	Uganda	1	0,75	0,05	0,69
154	Senegal	1	0,76	0,07	0,69

155	Indonesia	2	0,70	0,02	0,68
156	Cameroon	2	0,71	0,04	0,67
157	Cote d'Ivoire	2	0,70	0,03	0,66
158	Liberia	1	0,71	0,06	0,66
159	Guinea-Bissau	1	0,71	0,06	0,65
160	Burkina Faso	1	0,73	0,07	0,65
161	Guinea	1	0,78	0,13	0,65
162	DRC	1	1,00	0,36	0,64
163	Pakistan	2	0,68	0,04	0,63
164	Niger	1	0,74	0,13	0,62
165	Yemen	2	0,65	0,04	0,61
166	Sudan	2	0,62	0,03	0,59
167	Chad	1	0,65	0,07	0,58
168	Mauritania	2	0,59	0,04	0,55
169	Central African Republic	1	1,00	0,48	0,52
170	Afghanistan	1	0,54	0,03	0,51
171	Sierra Leone	1	0,54	0,03	0,51
172	Mali	1	0,56	0,06	0,50

Notes: DRC = Democratic Republic of the Congo, UK = United Kingdom, USA = United States of America, UAE = United Arab Emirates

S5. Sensitivity Analysis Results

To assess the robustness of the findings, given that DEA can produce sensitive results, an in-depth sensitivity analysis was performed. The following adjustments were made to determine the robustness of results:

1) The financial protection proxy, 1-OOPs/CHE, is substituted with GGHE-D/CHE, which is a similar and alternative proxy for financial protection;
2) 3 year lags for CHE were used in place of the 5 year lagged average to test the sensitivity of the time lag;
3) Outlying countries were removed one at a time, since deterministic models like DEA do not allow for random noise and are particularly sensitive to outliers
4) Conduct Tobit regression as second stage in place of Simar-Wilson.

1) Changing the CHE year

A 3-year average variable lagged by 5 years was applied in the main model to reflect the fact that changes in health expenditure are not reflected immediately in the outcomes. To test the robustness of the CHE variable, the main model was run with 5-year and 3-year lags from a single year. Small changes are made to the efficient set, but largely the results remain the same. No changes to the bias-corrected scores of >1% are observed. In the 3-year lag (CHE from 2012), Fiji and Madagascar are efficient in the DEA analysis prior to bias-correction and in the 5-year lag, Barbados becomes efficient. However, overall the model is robust to the choice of CHE variable.

2) Removal of outlier and efficient DMUs

Because DEA compares countries to their peers, the choice of peers made available can influence the results, particularly in the case of outliers who perform uniquely well. Therefore, to test whether any countries could be biasing the results, the Simar-Wilson regression and DEA was run individually excluding one country at a time. Countries to exclude were identified in three ways. Firstly, scatter plots and visual analysis identified nine potential outliers. Secondly, the five most extreme cases for the three input/output variables were identified using Nick Cox's extremes command on STATA. Finally, all countries with original DEA scores equal to one (fully efficient prior to bias-adjustment) were removed. Since many overlapped, this left a final set of 46 countries.

What happened to the bias-corrected efficiency scores?

Most countries have negligible changes (<5%) in the bias-corrected scores when removing others from the analysis. Notable exceptions are Niger, Gambia, CAR and Mali whose scores decrease by 10% when Vanuatu and Mozambique are removed, and DRC whose score increases by 10% when New Zealand is removed.

What happened to the double bootstrap regression results (determinants of efficiency)?

For all countries, the significant determinants of UHC provision efficiency remained the same when removing outliers – income, education and governance are significant.

3) Change in financial protection proxy to GGHE-D/CHE

Another measure of financial protection could be domestic general government expenditure as a proportion of current health expenditure. GGHE-D should be similar to 1-OOPs as it is the proportion of expenditure not attributed to OOP. The financial protection proxy indicator is therefore replaced by GGHE-D/CHE and the model is re-run. The results showed the exact same set in the high income group and some slight changes to the efficient sets of the other income groups, particularly the low income one. In this permutation, electricity access becomes a significant determinant of UHC efficiency and income is not significant at the 10% level.

Summary of 46 Sensitivity Analysis Graphs

There are only three cases in 46 models for 172 countries that have an average variation of more than 5% in the bias-corrected efficiency score. There are few examples where the removal of one outlier results in an up to 18% change. The largest variation is seen in the low income group. The main model is largely robust to removing outlier/efficient countries, changing the input to GGHE-D from 1-OOPs/CHE and changing the lag in CHE.

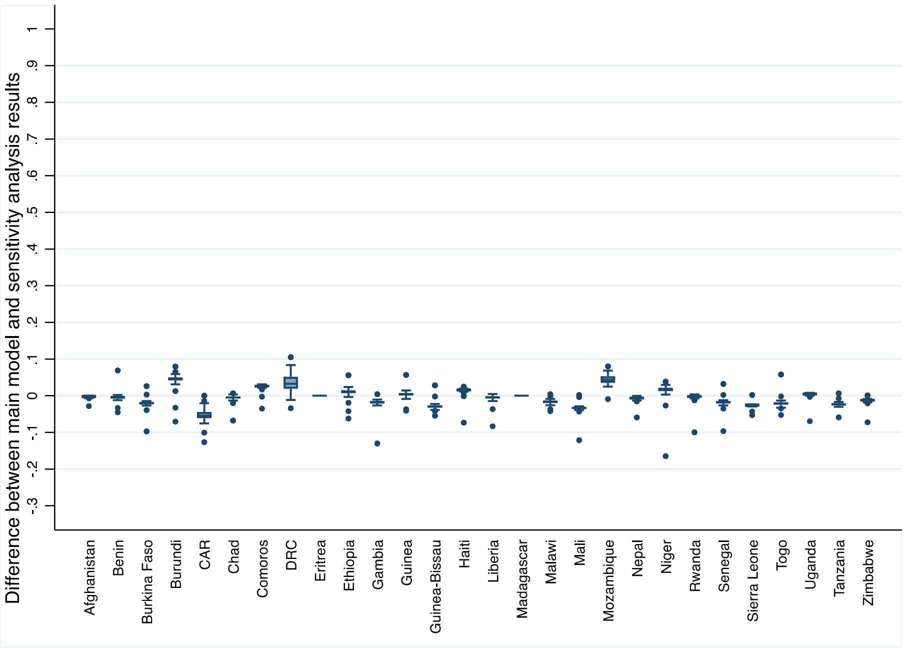


Figure 2: Summary of sensitivity analysis for low income countries

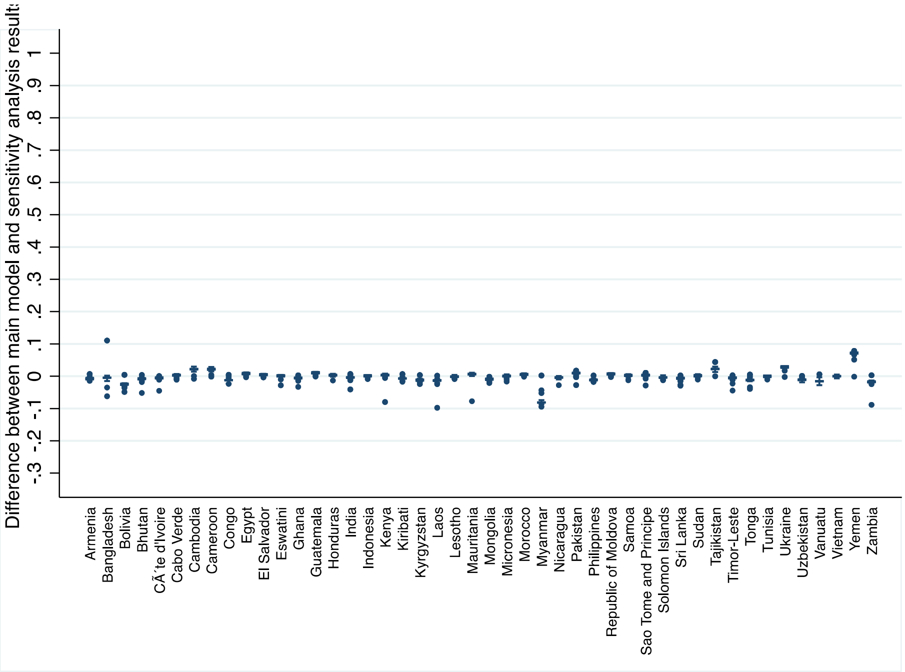


Figure 3: Summary of sensitivity analysis for lower-middle income countries

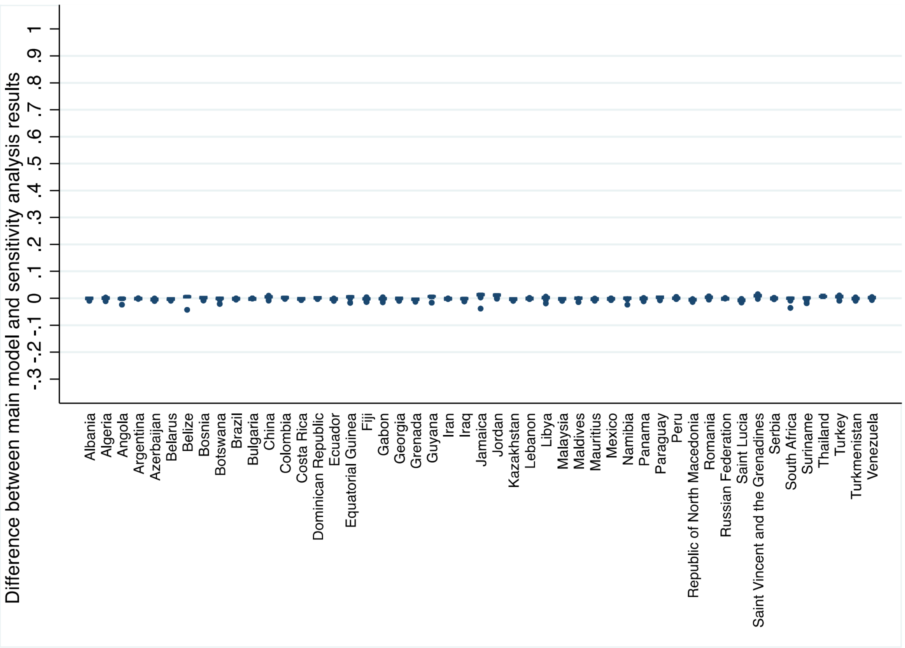


Figure 4: Summary of sensitivity analysis for upper-middle income countries

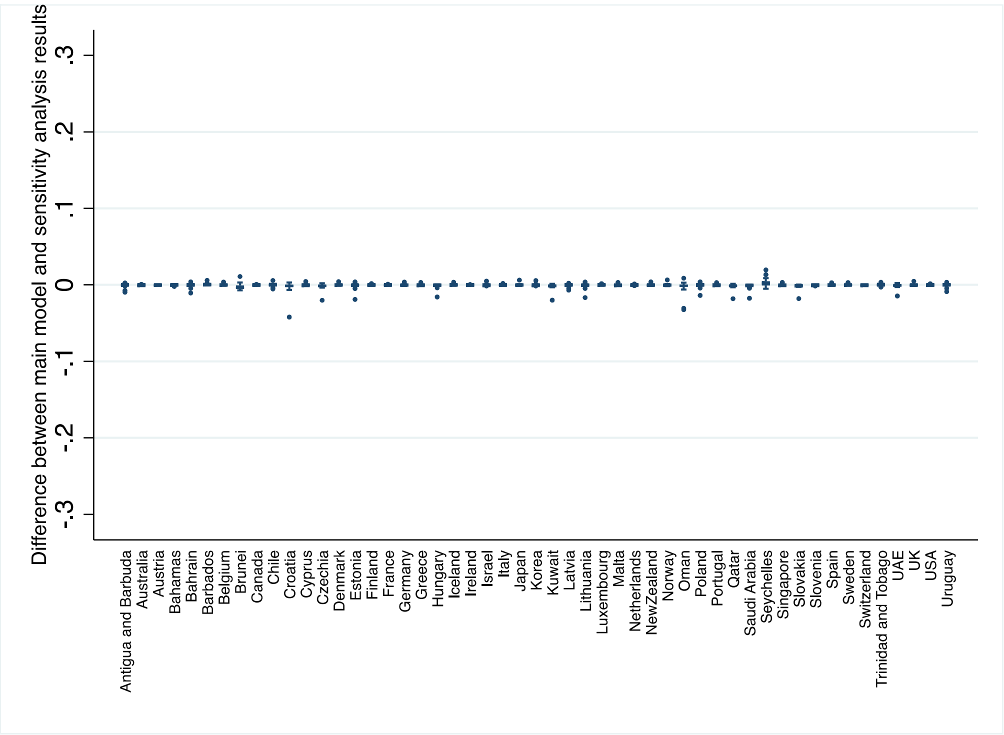


Figure 5: Summary of sensitivity analysis for high income countries

4) Tobit Regression in second-stage

Results using a Tobit regression instead of Simar-Wilson

Variable	**Coefficient (β)**	**Standard Error (σ)**	**95% Confidence Interval**	
			Lower Bound	**Upper Bound**
GDP	4.59×10^{-7}	4.40×10^{-7}	-4.09×10^{-7}	1.33×10^{-6}
EDUCATION	0.0144225***	0.0040104	0.0065034	0.0223416
ELECTRICITY	0.0010888***	0.0002952	0.000506	0.0016717
LOGPOP	-0.0051103	0.0031084	-0.0112482	0.0010276
POPDENSITY	1.35×10^{-6}	9.24×10^{-6}	-0.0000169	0.0000196
URBANPOP	-0.0000762	0.0003775	-0.0008216	0.0006692
GOVERNANCE	0.0275269*	0.0113006	0.0052124	0.0498414
HEALTHWORKER	0.0000572	0.0003135	-0.0005619	0.0006763
BEDS	0.0000859	0.0002909	-0.0004884	0.0006603
Constant	0.6132538***	0.046964	0.5205175	0.7059901

*p<0.05 **p<0.01, ***p<0.001

n=172