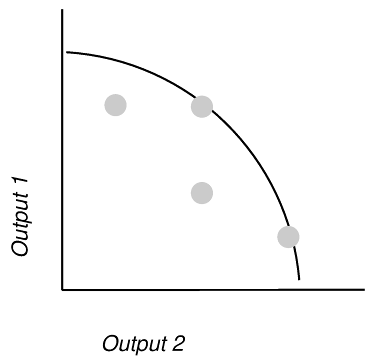
Supplementary Materials

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:

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

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

$$u_r, v_i \geq 0$$

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 $\widehat{\theta_i}$ for 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 $\mathbf{z}_i$ 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 $\widehat{\theta_i^b}$ for each DMU i=1, …, N, with b = 1, . . . , B_1.

> 3.1 For each DMU i = 1, . . . , N, draw an artificial error $\widetilde{\varepsilon_i}$ from the truncated N(0, $\hat{\sigma}$) distribution with left-truncation at $1 - \mathbf{z}_i\hat{\beta}$.
>
> 3.2 Calculate artificial efficiency scores $\widetilde{\theta_i}$ as $\mathbf{z}_i\hat{\beta} + \widetilde{\varepsilon_i}$ for each DMU i = 1, . . . , M.
>
> 3.3 Generate $i = 1, \ldots, N$ artificial DMUs with input quantities $\widetilde{x_i} = x_i$ and output quantities $\widetilde{y_i} = (\frac{\widehat{\theta_i}}{\widetilde{\theta_i}})y_i$.
>
> 3.4 Use the N artificial DMUs, generated in step 3.3, as reference set in a DEA that yields $\widehat{\theta_i^b}$ for each original DMU i = 1, …, M.

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

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 $\widehat{\theta_i^{bc}}$ on $\mathbf{z}_i$ 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 i = 1, …, N, draw an artificial error $\widetilde{\widetilde{\varepsilon}}$ 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.

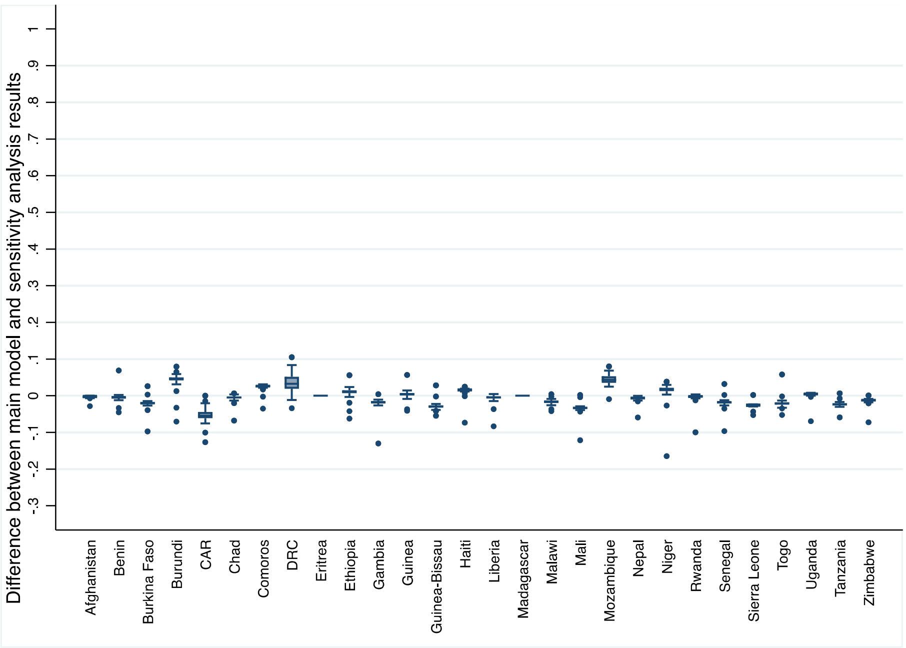


Figure 2: Summary of sensitivity analysis for low income countries

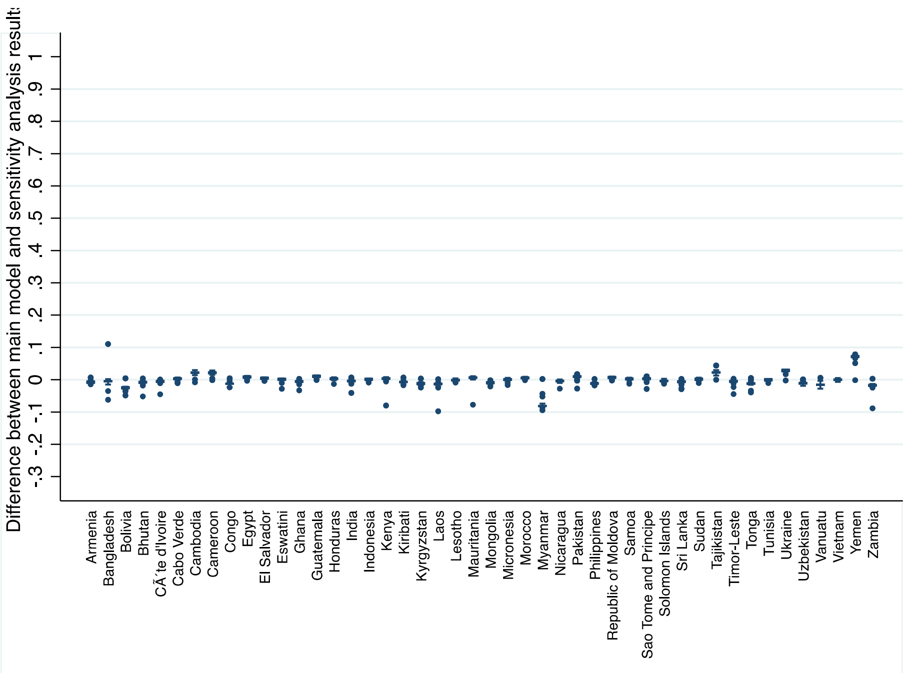


Figure 3: Summary of sensitivity analysis for lower-middle income countries

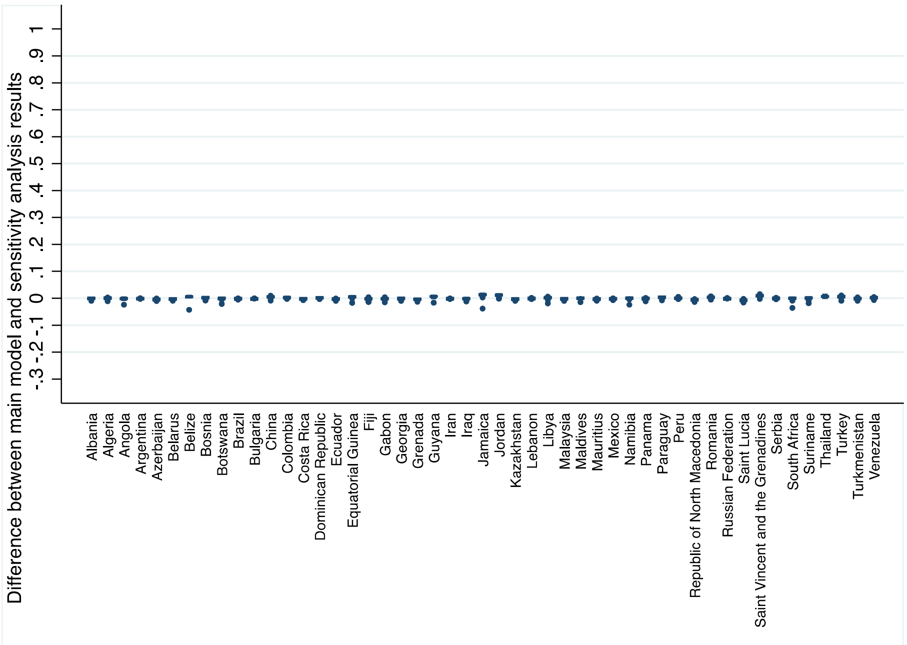


Figure 4: Summary of sensitivity analysis for upper-middle income countries

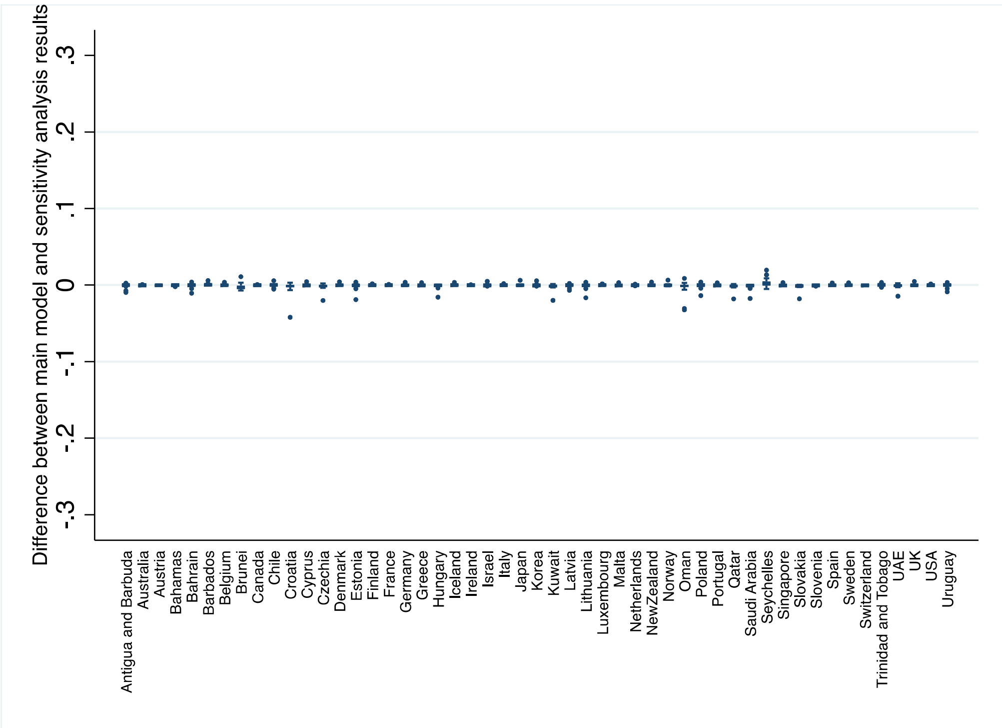


Figure 5: Summary of sensitivity analysis for high income countries

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