Global Healthcare Resource Efficiency in the Management of COVID-19 Death and Infection Prevalence Rates

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Abstract

The scale of impact that COVID-19 has on society and the economy globally, provides a strong incentive to thoroughly analyse the efficiency of healthcare systems in dealing with the current pandemic and learn some lessons that will help prepare healthcare systems to be better prepared for future pandemics. We use Data Envelopment Analysis (DEA) and data compiled from Worldometers (2020), and The World Bank (2020a, 2020b & 2020c) to analyse how efficient the use of resources were to stabilise the rate of infections and minimise death rates in 36 countries that represented 90% of global infections as at 11 November 2020. This is the first paper to model technical efficiency of countries in managing the COVID-19 pandemic by modelling death rates and infection rates as undesirable outputs using the approach developed by You & Yan (2011). We find that the average efficiency of global healthcare systems in managing the pandemic is very low, with only six efficient systems out of a total of 36 under the variable returns to scale assumption. This finding suggests that holding constant the size of their healthcare systems (because countries cannot alter the size of a healthcare system in the short run), most of the sample countries showed low levels of efficiency during this time of managing the pandemic; instead, it is suspected that most countries literally "threw" resources at fighting the pandemic, thereby probably raising inefficiency through wasted resource use.

JEL Classification: C6, D2, I1

Keywords: Pandemic; COVID-19; Death rates; Infection rates; Recoveries; Data Envelopment Analysis, Healthcare systems efficiency; Technical Efficiency; Undesirable outputs.

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1. Introduction

Since it first emerged in China in late December 2019, the new coronavirus (Covid-19) has spread to nearly every country of the world (Newey and Gulland, 2020). Within seven months, it had spread to 215 countries and regions. On 08 August 2020, Worldometers (2020) reported that more than 19.6 million people were known to be infected and more than 700,000 deaths had been recorded since the outbreak. Countries have adopted pandemic spread mitigating interventions referred to as non-pharmaceutical interventions (NPIs), such as social distancing, testing and contact-tracing, case isolation and public hygiene at an unprecedented scale (Correia et al. 2020).

Even with these drastic NPI interventions, the spread of the pandemic seems to have exploded, especially with surges in contagion experienced in countries like Italy, France the UK and the USA. This put immense strain on availability of especially ICU facilities and available doctors and nurses, and the efficiency of healthcare systems are put under the spotlight. What we learn from recent experiences in the fight against this deadly disease from countries like South Korea, is that accessibility to healthcare services can significantly reduce the number of deaths (Tang et al., 2020).

It is for this reason and the scale of impact that COVID-19 has on society and the economy globally, that the efficiency of healthcare systems need to be thoroughly examined in order to inform appropriate policy responses that will help prepare health systems globally to be better equipped when dealing with the next pandemic. We address this issue applying Data Envelopment Analysis (DEA) and extensive data compiled from Worldometers (2020), and The World Bank (2020a, 2020b & 2020c). Specifically, we analyse the efficient use of available resources to stabilise the rate of infections and minimise the case-fatality rates in selected 36 countries comprising 90% of global infections as at 11 November 2020. Our initial sample was overtaken by events. These countries also account for 67% of recoveries and 92% of global deaths (Worldometer 2020). Our contribution to the literature is twofold: First, this paper is the first that models technical efficiency of countries in dealing with the COVID-19 pandemic by modelling death rates and infection rates as undesirable outputs and, second, modelling comparative scenarios to test the accuracy of our model.

2. Literature review

DEA has been applied extensively to compare efficiency of health care facilities within countries and between countries, and we briefly deal with some of that literature here. We do not deal with the literature on country studies because our paper compares efficiency between countries. For literature on efficiency studies among different healthcare facilities within a country, see for example Ngobeni, et al. (2020); Campanella et al. (2017); Alhassan et al. (2015); Jarjue et al. (2015); Chowdhury et al. (2010); Gannon (2005); Marschall and Flessa (2009); Akazili et al. (2008); Masiye (2007); Zere et al. (2006); Kirigia et al. (2001); and Kirigia et al. (2000).

Although healthcare is one of the most popular areas of application for DEA (Liu et al. 2013), DEA studies on healthcare systems worldwide are still limited. For example, Bhat (2005) used DEA to measure the impact of financial and institutional arrangements on national healthcare system efficiency in 24 OECD countries. Lo Storto and Goncharuk (2017) applied DEA to measure the technical efficiency of 32 European (EU) countries. Afonso and St Aubyn (2006) used a two-stage DEA to estimate a semi-parametric model of the healthcare systems in 30 OECD countries the years 1995 and 2003. De Cos and Moral-Benito (2014) estimated alternative measurements of efficiency using DEA and SFA between 1997 and 2009 to ascertain the most important determinants of healthcare efficiency across 29 OECD countries. Hadad et al. (2013) compared healthcare system efficiency of 31 OECD countries with two model specifications, one including inputs under management control and the other inputs beyond management control. Kim and Kang (2014), used a bootstrap DEA to estimate efficiency of healthcare systems in a sample of 170 countries.

Although the choice of inputs is similar in these studies, outputs selection depends mostly on the purpose of the research. For example, Gonzalez et al. (2010), in a cross-sectional study measured the technical and value efficiency of health systems in 165 countries. They used expenditure on health and education as inputs and data on healthy life expectancy and disability adjusted life years as health outcomes. Examining the efficiency in healthcare services delivery to the population, Bhat (2005) uses the number of populations aged 0-19 years, 20-64, and 65 or older as outputs. Santos et al. (2012) examine the efficiency of countries in preventing the mother-to-child HIV transmission and used the number of pregnant women tested for HIV and the number of HIV pregnant women receiving antiretroviral drugs as outputs.

DEA studies for new settings such as the recent COVID-19 outbreak may however need to introduce new outputs. Shirouyehzad et al. (2020) uses DEA to analyse the efficiency of contagion of COVID19 and focus on the number of deaths and recoveries as outcomes. Breitenbach, et al, (2020), analyse the 31 most infected countries during the first 100 days since the outbreak of the COVID-19 coronavirus for the efficiency in containing the spread of the virus and focus on flattening the curve as the main output. Empirical work pivots mostly on healthcare system performance based on technical efficiency calculated as a ratio of some quality of life variable as an output and physical health resources or expenditure on health as inputs. The inputs most used were expenditure, doctors and nurses while the outputs were discharge or recovery, prevalence and mortality rates. In this paper we use tests, doctors and nurses as physical inputs and health spending as financial input in managing the COVID-19 pandemic. As outputs we use case-fatality (deaths) and infection prevalence rates.

3.1. Methodology

In this paper, we use the variable returns to scale (VRS) approach reported by Gavurova et al. (2017) and developed in 1984 by Banker, Charnes and Cooper (BCC model) to allow for consideration of scale efficiency analysis. Envelopment in DEA refers to the ability of the efficiency production frontier to tightly enclose the production technology (input and output variables). According to Cooper et al. (2007) and McWilliams et al. (2005), DEA was developed in a microeconomic setting and applied to firms to measure the efficiency of converting inputs into outputs. In the analysis of public institutions, firms are replaced by the more encompassing decision-making units (DMU). DEA is therefore an appropriate method of computing the efficiency of institutions employing multivariate production technologies. Aristovnik (2012) and Martić et al. (2009), distinguish between input-minimisation and output-maximisation DEA models. The former determines the quantity of inputs that could be curtailed without reducing the prevailing level of outputs and the latter expands the outputs of DMUs to reach the production possibility frontier while holding the inputs constant. However, the selection of each orientation is study-specific. In this paper, we select the input minimisation orientation.

According to Taylor and Harris (2004), DEA is a comparative efficiency measurement tool that evaluates the efficiency of homogeneous DMUs operating in similar environmental conditions, for example, DMUs dealing with COVID-19 and where the relationship between inputs and outputs is unknown. We follow Joumard et al. (2008) to treat the whole healthcare system in a given country as a DMU in order to analyse the healthcare system at the aggregate level. We also adopt the VRS methodology in this study because of heterogeneity among the DMUs in terms of factors like country size and income. In terms of the DEA methodology, the current study uses the BCC model with the ratio of DMUs being 4 times the combined number of inputs and outputs to ensure the stability of the efficiency results.

3.2. Modelling undesirable outputs

DEA models have found increasing use in efficiency analysis applications where at least one output in the production process is an undesirable output, e.g. pollution. There is considerable research published on the undesirable aspects of production outputs. However, You and Yan (2011) have found that the economic implications and the suitability of DEA models incorporating the undesirable outputs should be carefully considered as the results may either under- or overstate efficiency if modelled incorrectly.

The first way that undesirable outputs are dealt with in the traditional DEA model, is to ignore the undesirable output (Nakashima et al, 2006; Hua and Bian, 2007; Lu and Lo, 2007a, b). It is not however, appropriate to ignore the reality of e.g. pollution during production since undesirable outputs and desirable outputs are generated simultaneously in the production process. Dyckhoff and Allen (2001) dealt with undesirable outputs by modelling them as inputs. However, treating undesirable outputs as inputs fails to reflect the true production process. There is a specific production technology that links inputs to outputs, and taking an undesirable output as an input in the production process leads to misspecification and misinterpretation, for example, when modelling the pollution as an input using an output-oriented measure, ecological inefficiencies remain undetected. Golany and Roll (1989) suggested a data transformation approach where an undesirable output is converted into a 'normal' output by a monotonic decreasing function. The undesirable outputs (carbon and nitrogen emissions) are treated as normal outputs by taking their reciprocals. Although the pollutant is treated as output, the scale and intervals of the original data get lost and problem with zero values is that it does not have a reciprocal value. The Linear monotonic decreasing transformation was suggested by Seiford and Zhu (2002). A sufficiently large positive scalar βi is added to the reciprocal additive transformation of the undesirable output i so that the final values are positive for each DMU_k. This model is criticised for its invariance to data transformation within the DEA model (Lu and Lo, 2007a, b). Färe et al., (1989) treats undesirable factors in a non-linear DEA model based on the weak disposability of undesirable outputs (Zhou et al, 2007). Weak disposability assumes that to reduce undesirable outputs it is costly because simultaneously, it increases the inputs or decreases desirable outputs (Yang et al, 2008). It tends to increase the desirable output and undesirable output at the concurrently. Regardless of the form of transformation, as long as the final value of undesirable output included in the DEA calculation remains positive, it increases the efficiency of the DMU. An undesirable output should bring either a negative or positive impact to the performance of DMU; therefore it is not appropriate for the undesirable output to solely favour the efficiency score.

After comparing the performance of the models discussed above, You and Yan (2011) developed the ratio model, which outperformed all five of these models developed for dealing with undesirable outputs. We therefore opted to adopt the ratio model for the current paper. The ratio model is different from the previous approaches in that the undesirable output is aggregated in a ratio form with the desirable output.

From the conventional BCC DEA model and assuming that there are R DMU$_r$ ($r = 1, 2, \ldots, R$), that convert m inputs to n outputs, DMU$_k$ is one of the R DMUs being evaluated. It is further assumed that DMU$_k$ consumes m inputs X_t^k ($i = 1, 2, \ldots, m$) to produce n outputs Y_j^k ($j = 1, 2, \ldots, n$) and all these outputs are assumed to be desirable. The measure of efficiency of DMU$_k$ is then obtained by:

min θ subject to

$$\sum_{r=1}^{R} \lambda_r X_i^r - \theta X_i^k + s_i^- = 0 \qquad i = 1, 2, \ldots, m$$

$$\sum_{r=1}^{R} \lambda_r Y_j^r - s_j^+ = Y_j^k \qquad j = 1, 2, \ldots, n$$

$$\sum_{r=1}^{R} \lambda_r = 1$$

$$\lambda_r, s_i^-, s_j^+ \geq 0 \qquad r = 1, \ldots, R \tag{3}$$

where DMU$_r$ = the rth DMU, $r = 1, 2, \ldots, R$; DMU$_k$ = the kth DMU being evaluated; X_i^r, Y_j^r = the inputs and outputs of every DMU$_r$; $i = 1, 2, \ldots, m$, j = 1,2, . . . , n; θ = the efficiency of DMU$_k$; λ_r = the dual variable corresponding to the other inequality constraint of the primal; s_i^-, s_j^+ = the slack variables that turn the inequality constraint into an equal form; λ_r^*, s_i^{-*}, s_j^{+*} = the optimal solutions when the relative efficiency of DMU$_k$ is $\theta^* = 1$ and $s_i^{-*} = s_j^{+*} = 0$.

In the ratio model, the undesirable output and desirable output are defined as O_q^- ($q = 1.2, \ldots, n_1$) and O_p^+ ($p = 1, 2, \ldots, n_2$), respectively ($n_1 + n_2 = n$). For DMU$_k$, the undesirable outputs $O_q^-(q = 1, 2, \ldots, n_1)$ are treated as a new variable ψ_k, which is called the penalty parameter and is written as:

$$\psi_k = \rho_1 O_{1k}^- + \cdots + \rho_{n1} O_{n1k}^- \tag{4}$$

where ψ_k = penalty parameter for DMU$_k$; ρ_q = the penalty for individual undesirable output ($q = 1, 2, \ldots, n_1$); O_q^- = the undesirable output ($q = 1, 2, \ldots, n_1$). Since ρ_q is the penalty charged for producing the outputs, the ψ_k obtained from problem (4) gives a measure of the total monetary value of undesirable outputs. From the definition of ψ_k, the greater the amount of undesirable output, the greater is the value of the penalty parameter. Further, the respective value of ρ_q is associated with the individual undesirable output, therefore ρ_q has the same value for every DMU. With this model, desirable and undesirable outputs can relate to one another, regardless of disagreement in the units. With the new approach of treating the undesirable outputs in (4), the desirable output $p\,(p = 1, 2, \dots, n_2)$ of DMU_k in the ration model is modified as :

$$Y'_\rho = \frac{1}{\psi_k} O_p^+, \qquad (p = 1, 2, \dots, n_2) \qquad (5)$$

where O_p^+= the desirable output $(p = 1, 2, \dots, n_2)$; Y'_ρ = the modified output $(p = 1, 2, \dots, n_2)$. The ratio model computes desirable and undesirable outputs as fractions, where undesirable output O_q^- is the denominator and desirable output O_p^+ the numerator. Here the value of the output is interpreted as a ratio of desirable to undesirable output. Using ratios provides a simple and easy way to expose the impact of undesirable outputs in a DEA. The ratio form of the DEA model can satisfy the restrictions of the conventional DEA, which the output variable states must be a positive value. Moreover, the ratio form provides a more distinct way for the desirable and desirable output to describe the presence of an undesirable output on DMU efficiency.

In order to check the stability of our model results, we ran three different model specifications and compared the results. In Model I, we use the number of tests and number of doctors and nurses as physical inputs, health expenditure as financial input and as output the ratio of recoveries to infection rates (ratio of desirable to undesirable output). In Model II, we use the number of tests and number of doctors and nurses as physical inputs, health expenditure as financial input and as output the ratio of recoveries to death rates (ratio of desirable to undesirable output) and in Model III, we use the number of tests and number of doctors and nurses as physical inputs, health expenditure as financial input and as output the number of recoveries. In Model III we therefore ignore the undesirable outputs (Nakashima et al, 2006; Hua and Bian, 2007; Lu and Lo, 2007a, b). Although it is not good to ignore the undesirable outputs of the rate of new infections and death rates, we do this in order to compare the difference that the inclusion of the undesirable outputs in our model has on the efficiency scores.

3.3. Data

Our data are gathered from different sources. The COVID-19 related data (i.e. Infected Cases, Recovered Cases and Deaths and number of tests) are extracted from extensive data compiled from Worldometers (2020). Aggregated data on Doctors and Nurses per

100 000 of the population, and healthcare expenditure were obtained from World Development Indicators (WDI) provided by The World Bank (2020a, 2020b & 2020c).

Table 1: Descriptive statistics and variables used in the model

Variables	Unit	Mean	Standard Deviation	Minimum	Maximum
Physical Inputs					
No. of Tests	per million of the population	200849.78	159220.81	15033.00	541193.00
No. of Doctors & Nurses	per 1000 of the population	7.00	5.00	1.00	22.00
Financial Input					
Health expenditure	% of GDP	8.00	3.00	3.00	17.00
Desirable output					
Recovery Rate	No. of people	974486.67	1844065.41	30504.00	8023412.00
Undesirable outputs					
Death Rates	No. of People	32820.67	50619.93	1174.00	245989.00
Infection Rates	No. of People	1295119.31	2265355.91	175711.00	10575373.00

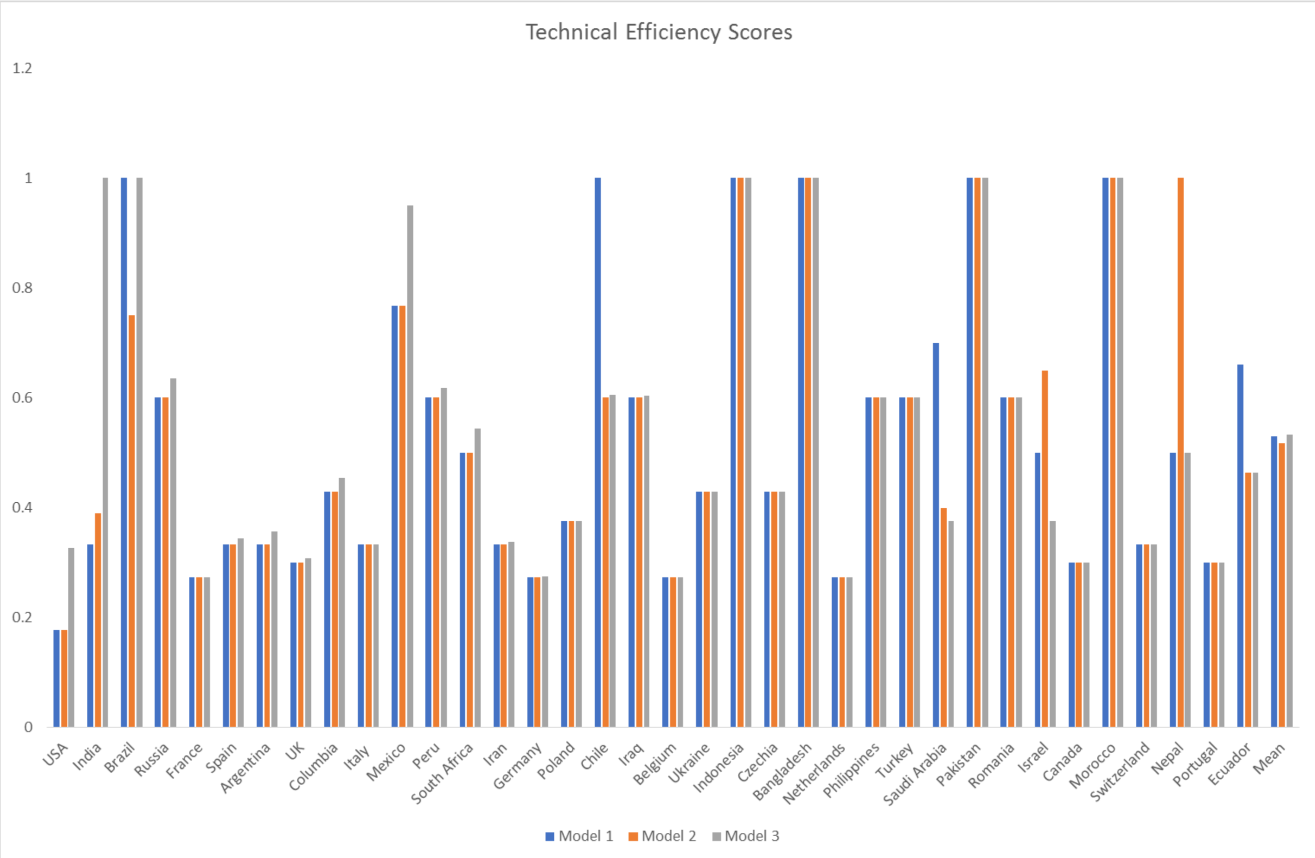
Some descriptive statistics of those variables are reported in Table I indicate that our sample countries have, on average, a resource of nearly seven doctors and nurses per 1000 of the population, a budget of about 17% of GDP and 200 850 tests per 1 million of the population for its healthcare system. The number of infected cases and deaths from COVID-19 over the study period averaged more than 1 295 120 and 32 821, respectively; and the mean number of people recovering from the infection around 974 487 persons. Assuming that the whole healthcare system is mobilised to fight the COVID-19 outbreak, how efficient was the mobilisation of resources? This issue is analysed with our DEA model and the results reported in the next section.

4. Results

The results of the three model variants is graphically illustrated in Figure 1 and the results in Table 1 (Annexure). As intimated earlier in this paper, it is important to consider the VRS technical efficiency scores motivated by the differences in the size of healthcare systems globally, particularly between large developed economies and small less-developed economies. The VRSTE are almost identical across the three model variants. This points to two things: First, the inclusion of undesirable outputs in our model (variants I and II), does not have any material impact on the mean technical efficiency of country healthcare systems, and second, it points to the stability of our results across the three model variants. For the sake of simplicity, we therefore discuss only the results reflected in Model I, where our physical inputs were the number of tests/million of the population and number of doctors and nurses per 100 000 of the population; our financial input healthcare expenditure as a percentage of GDP and our output recoveries/infections. Under the CRS assumption, there were only two efficient healthcare systems in dealing with COVID-19, viz. Bangladesh and

Pakistan. When the VRS assumption is considered, the figure rises as expected, in this case to six, with the addition of Brazil, Chile, Indonesia and Morocco.

Figure 1: CRS and VRS efficiency scores of global healthcare systems



	Model I: Output - recoveries/infection			Model II: Output - recoveries/deaths			Model III: Output - Recoveries		
	CRSTE	VRSTE	SE	CRSTE	VRSTE	SE	CRSTE	VRSTE	SE
Mean	0.43	0.53	0.76	0.3	0.52	0.51	0.14	0.53	0.22
Standard deviation	0.27	0.256	0.233	0.266	0.244	0.27	0.235	0.256	0.258
Maximum	1	1	1	1	1	1	1	1	1
Minimum	0.03	0.18	0.11	0.01	0.18	0.03	0	0.27	0.01
No. of Efficient	2	6	10	2	5	2	2	6	2
No. of Inefficient	34	30	26	34	31	34	34	30	34

Note: *CRSTE* represents technical efficiency under constant returns to scale assumption; *VRSTE* represents technical efficiency under variable returns to scale assumption; and *SE* represents scale efficiency.

Source: Authors' graph from results

These differences, regarding the full sample of 36 countries, are statistically significant under a Mann-Whitney-Wilcoxon's test (Z = 5.271, p = 0.001). It indicates the role of scale efficiency (*SE*) in our analysis because it is the objective of the global healthcare systems to achieve the optimal technical combination of the inputs to produce the outputs, but their scales (sizes) are not optimal yet. Although 21 of the 36 countries in our sample are operating under increasing returns to scale, the technical combination of inputs to produce the existing output is still not optimal. Six of the 36 countries operate under decreasing returns to scale (see the Appendix), suggesting that they can double their inputs without doubling their output. These countries could therefore rationalise their healthcare resources/inputs by downsizing (using resources/inputs more efficiently) and, thereby, improving the technical efficiency, while the outputs can still stay the same. At first glance it is often difficult to envisage a country with a large undesirable output to be technically efficient. Brazil for example, has a very high number of infections and deaths, yet our DEA results show that Brazil is technically efficient and lies on the efficiency frontier. To gain further insight into this number and the associated DEA efficiency scores, it is helpful to compare inputs and outputs of a benchmark country like Brazil, relative to that of other countries. We have done this in Table 2.

Table 2: Inputs and outputs relative to benchmark country (Brazil)

Country	VRSTE	Expenditure (% of GDP)	Doctors & Nurses/100 000	No. of Tests	Infections	Deaths	Recoveries
Brazil	1	4	4	102,766	5,701,283	162,842	5,964,344
USA	0.18	17	14	484,227	10,575,373	245,989	6,603,470
France	0.27	11	14	279,353	1,829,659	42,207	131,920
Germany	0.27	11	17	278,886	710,265	11,912	454,800
Belgium	0.27	11	14	458,403	507,475	13,561	30,504
Comparison with Brazil							
USA/Brazil		4.25	3.5	471.19%	185.49%	151.06%	110.72%
France/Brazil		2.75	3.5	271.83%	32.09%	25.92%	2.21%
Germany/Brazil		2.75	4.25	271.38%	12.46%	7.32%	7.63%
Belgium/Brazil		2.75	3.5	446.06%	8.90%	8.33%	0.51%

Source: Calculated from Table 3 results

For example, in comparison to Brazil, the USA spends 4.25 times more as a percentage of GDP on Healthcare, has 3.5 times more doctors and nurses per 100 000 of the population, and had 471% more COVID-19 tests performed relative to Brazil; yet it did not succeed to contain its undesirable outputs (Infections are 185% higher and deaths 151% higher than Brazil) even though it performed well in the area of the good output, recoveries. This result clearly explains the relatively low VRS technical efficiency scores of the USA, France, Germany and Belgium in Table 2, which could be linked to specific policy responses of selected countries. For example, evidence now suggests that the UK failed to fight the COVID-19 outbreak by following a 'herd immunity' approach (Stewart *et al.*, 2020) and the USA was very slow to act against COVID-19 (Watts, 2020).

5. Conclusions

This paper examined the efficiency of 36 healthcare systems (which represent 90% of cases globally) in managing the COVID-19 pandemic, given their resources constraints. We use a novel DEA approach, developed by You and Yan (2011), which accounts for both desirable outputs (recovered cases) and undesirable outputs (infections and deaths) and our results indicate that the average efficiency of global healthcare systems in managing the COVID-19 pandemic is very low, with only six efficient systems out of a total of 36 under the variable returns to scale assumption. This finding suggests that holding constant the size of their healthcare systems (because countries cannot alter the size of a healthcare system in the short run), most of the sample countries could not improve their efficiency during this time of managing the pandemic; instead, it is suspected that most countries literally "threw" resources at fighting the pandemic, thereby probably raising inefficiency through wasted resource use. The study also showed that developed countries could also draw lessons from developing countries in the management of pandemics. The latter countries mostly face pandemics on a daily basis, therefore, have developed strategies for efficiently managing them.

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Annexure A: Table 3: Analytical variables and efficiency scores

		Model I				Model II				Model III			
DMU #	**Country**	**CRS efficiency score**	**VRS efficiency score**	**Scale**	**Type of scale**	**CRS efficiency score**	**VRS efficiency score**	**Scale**	**Type of scale**	**CRS efficiency score**	**VRS efficiency score**	**Scale**	**Type of scale**
1	USA	0.12	0.18	0.67	IRS	0.07	0.18	0.39	IRS	0.29	0.33	0.89	DRS
2	India	0.33	0.33	1.00	-	0.38	0.39	0.96	DRS	1.00	1.00	1.00	-
3	Brazil	0.83	1.00	0.83	DRS	0.40	0.75	0.54	IRS	1.00	1.00	1.00	-
4	Russia	0.47	0.60	0.78	IRS	0.37	0.60	0.62	IRS	0.18	0.64	0.29	IRS
5	France	0.03	0.27	0.11	IRS	0.01	0.27	0.04	IRS	0.01	0.27	0.03	IRS
6	Spain	0.22	0.33	0.67	IRS	0.11	0.33	0.33	IRS	0.07	0.34	0.19	IRS
7	Argentina	0.33	0.33	1.00	-	0.16	0.33	0.48	IRS	0.16	0.36	0.46	IRS
8	UK	0.20	0.30	0.67	IRS	0.07	0.30	0.22	IRS	0.05	0.31	0.17	IRS
9	Columbia	0.43	0.43	1.00	DRS	0.22	0.43	0.50	IRS	0.16	0.45	0.34	IRS
10	Italy	0.15	0.33	0.44	IRS	0.04	0.33	0.13	IRS	0.03	0.33	0.08	IRS
11	Mexico	0.67	0.77	0.87	IRS	0.11	0.77	0.14	IRS	0.40	0.95	0.42	IRS
12	Peru	0.60	0.60	1.00	-	0.21	0.60	0.35	IRS	0.15	0.62	0.24	IRS
13	South Afric	0.50	0.50	1.00	-	0.30	0.50	0.61	IRS	0.13	0.54	0.24	IRS
14	Iran	0.26	0.33	0.78	IRS	0.07	0.33	0.22	IRS	0.09	0.34	0.27	IRS
15	Germany	0.18	0.27	0.67	IRS	0.15	0.27	0.55	IRS	0.03	0.27	0.10	IRS
16	Poland	0.17	0.38	0.45	IRS	0.15	0.38	0.41	IRS	0.03	0.38	0.07	IRS
17	Chile	0.67	1.00	0.67	DRS	0.30	0.60	0.49	IRS	0.09	0.61	0.15	IRS
18	Iraq	0.60	0.60	1.00	-	0.37	0.60	0.62	IRS	0.09	0.60	0.15	IRS
19	Belgium	0.03	0.27	0.11	IRS	0.01	0.27	0.03	IRS	0.00	0.27	0.01	IRS
20	Ukraine	0.24	0.43	0.55	IRS	0.16	0.43	0.36	IRS	0.03	0.43	0.07	IRS
21	Indonesia	0.95	1.00	0.95	IRS	0.44	1.00	0.44	IRS	0.23	1.00	0.23	IRS
22	Czechia	0.29	0.43	0.67	IRS	0.32	0.43	0.75	IRS	0.03	0.43	0.06	IRS
23	Bangladesh	1.00	1.00	1.00	-	1.00	1.00	1.00	-	0.43	1.00	0.43	IRS
24	Netherlands	0.18	0.27	0.67	IRS	0.13	0.27	0.46	IRS	0.02	0.27	0.07	IRS
25	Philippines	0.60	0.60	1.00	-	0.46	0.60	0.77	IRS	0.08	0.60	0.14	IRS
26	Turkey	0.60	0.60	1.00	-	0.27	0.60	0.45	IRS	0.05	0.60	0.09	IRS
27	Saudi Arabi	0.42	0.70	0.60	DRS	0.33	0.40	0.83	IRS	0.04	0.38	0.10	IRS
28	Pakistan	1.00	1.00	1.00	-	0.82	1.00	0.82	IRS	0.16	1.00	0.16	IRS
29	Romania	0.47	0.60	0.78	IRS	0.23	0.60	0.38	IRS	0.03	0.60	0.05	IRS
30	Israel	0.42	0.50	0.83	DRS	0.63	0.65	0.97	IRS	0.03	0.38	0.07	IRS
31	Canada	0.27	0.30	0.89	IRS	0.09	0.30	0.30	IRS	0.02	0.30	0.05	IRS
32	Morocco	0.89	1.00	0.89	IRS	0.88	1.00	0.88	IRS	0.02	1.00	0.02	IRS
33	Switzerland	0.19	0.33	0.56	IRS	0.19	0.33	0.58	IRS	0.01	0.33	0.03	IRS
34	Nepal	0.44	0.50	0.89	IRS	1.00	1.00	1.00	-	0.03	0.50	0.07	IRS
35	Portugal	0.20	0.30	0.67	IRS	0.16	0.30	0.52	IRS	0.01	0.30	0.02	IRS
36	Ecuador	0.52	0.66	0.79	DRS	0.10	0.46	0.21	IRS	0.05	0.46	0.11	IRS
Mean		0.43	0.53	0.76		0.30	0.52	0.51		0.14	0.53	0.22	
# of effic. DMUs		2	6	10		2	5	2		2	6	2	

Sources: Authors’ Table based on DEA efficiency calculated results.