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Assessing the Efficiency of Public Health and Medical Care Services in Curbing the COVID-19 Pandemic in Sub-Saharan Africa: A Retrospective Study

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Abstract

In the late of December 2019, a new coronavirus (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV 2) emerged from the city of Wuhan, China and was subsequently declared a pandemic by the World Health Organization (WHO) on March 11, 2020 after it had spread to many countries across the globe. On February 28, 2020, the Sub-Saharan Africa (SSA) reported its first case in Nigeria, and it has since spread to all countries in SSA. Several public health and medical care measures were rolled out by many countries to stem the tide of the spread at the height of the pandemic, between February 28, 2020 and February 28, 2021, period covered by this study. This paper evaluates the levels of health system efficiency of the COVID-19 public health measures and medical care services and their determinants across Sub-Saharan African (SSA) countries using country-level data for those countries. The data was analyzed using bootstrap data envelopment analysis (DEA) and other advanced econometric analyses that produce robust estimations of the relationship between health systems efficiency and their determinants. The general finding of the study suggests that there is more room for health systems in SSA to improve their technical efficiency in fighting the COVID-19 pandemic. The most important determinants of health system efficiency in the fight against the spread of the virus were GDP per capita, population density, temperature levels, and quality of governance. Adequate health system preparedness and human resource strategies geared towards recruiting and/or retaining well-qualified and experienced healthcare workers to provide professional services would prove critical in containing pandemics of this nature.

Keywords: COVID-19, Health systems, Public health, Medical care, Data envelopment analysis, Sub-Saharan Africa

1. Introduction

In the late of December 2019, a new coronavirus (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV 2) emerged from the city of Wuhan, Hubei Province in the People's Republic of China (Arshad Ali et al., 2020), on December 29, 2019, when a cluster of pneumonia of unknown origin occurred (The 2019-nCoV Outbreak Joint Field Epidemiology Investigation Team, 2020). On February 28, 2020, the Sub-Saharan Africa (SSA) reported its first case in Nigeria (Adepoju, 2020), and it has since spread to all the 46 SSA countries. It was subsequently declared a pandemic by the World Health Organization (WHO) on March 11, 2020 after it had spread to many countries and regions across the globe (Mahase, 2020). Health System Strengthening in Sub-Saharan Africa (ASSET) on January 16, 2021 reported that more than 2.2 million people in Africa have been confirmed to be infected and more than 50,000 deaths recorded (ASSET, 2021). Many health systems in the SSA region are limited in their ability to respond robustly to this pandemic due to decades of under-investment in healthcare, relying heavily on out-of-pocket payment and donor support. Out of 46 countries in the SSA region 41 are classified as having weak health systems, languishing in the bottom 5th of countries worldwide ranked by Healthcare Access and Quality (Fullman et al., 2018).

Even though the younger age distribution and warmer temperature in the SSA region are factors recognized to potentially mitigate the effect of COVID-19 (Kissler, Tedijanto, Goldstein, et al., 2020; Chiyomaru and Takemoto, 2020), the fragile nature of the health systems in the region and many other factors may perhaps combine to worsen the severity of the COVID-19 pandemic, viz.: larger household sizes, intergenerational mixing within households, overcrowded urban settlements, inadequate water and sanitation facilities, severe shortages of intensive care beds and ventilators, high prevalence of undiagnosed and unmanaged pre-existing diseases such as diabetes, tuberculosis, and HIV/AIDS (Zandvoort et al., 2020; Gilbert, Pullano, Pinotti, et al., 2020; The Economist, 2020; Bishop, 2020). It is, therefore, imperative for countries in the sub-region to attenuate the spread of the virus to ensure that health systems can cope with patient numbers and that mortality rates are reduced to the barest minimum.

The absence of mass vaccination in the SSA countries (as at the time of conducting this study), leaves policy makers with limited policy options that largely entail measures to restrict movement and physical interaction of people (i.e. non-pharmaceutical interventions (NPIs)) in order to curb exponential spread of the virus. NPIs usually involve social-distancing measures, border closures, self-isolations of symptomatic patients and public hygiene, and in extreme cases stringent lockdown measures (Correia et al., 2020). Governments across the SSA sprang into action and began rolling out an extensive social distancing measures after the first few cases of COVID-19 were confirmed (Osseni, 2020). Health officials in countries such as Nigeria, Rwanda, Ghana, Benin, South Africa, and Ethiopia embarked on vigorous tracing and testing of people whom COVID-19 patients had contact with. Soon after that most of these countries came up with innovative technology like Mobile Location Data Tracking to lessen the laborious human effort in tracing people who had come into contact with COVID-19 patients (Ekong, Chukwu, Chukwu, 2020). When these initial NPI measures failed to contain the contagion, isolation centers were set up, borders and schools in many SSA countries were closed, and full lockdowns were implemented in some countries while others were partially locked-down to contain the spread (Haider, Osman, Gadzekpo, et al., 2020).

Evidence shows that the speed with which governments implement NPIs determines, to a large extent, how well the spread of the COVID-19 contagion would be contained (Zandvoort et al., 2020). Large amount of resources were expended between February 28, 2020 and February 28, 2021, period covered by this study, to carry through the NPI measures. Besides the direct material and labour cost, the World Bank estimated that COVID-19 pandemic would cost the SSA region between \$37 billion and \$79 billion in output losses, translating into a decline of between 2.1% and 5.1% of GDP, due to economic disruptions caused by this global pandemic (Toure, 2020). The question of whether the resources directed towards curbing the spread of COVID-19 were used efficiently in the SSA region remains unanswered. This study seeks to fill this void in the literature.

The rest of the paper is organized as follows: Section 1.2 reviews the literature on health system efficiency and COVID-19 pandemic. Section 2 covers the applied methodology and estimation procedures used. It presents detailed explanation on the choice of variables, methods and models used in estimation of health system efficiency in the fight against COVID-19 pandemic. Section 3 presents and discusses the empirical results of the technical efficiency scores, consequent rankings, as well as the major determinants of health systems efficiency. The final section, Section 4, presents the conclusions, recommendations, and limitations of the study as well as implications for further studies.

1.2 Literature Review

From the accessible literature, only two studies have been carried out on health system efficiency in curbing the spread of the COVID-19 virus (Shirouyehzad et al., 2020 and Breitenbach et al., 2020). Shirouyehzad et al. (2020) analyzed the efficiency performance of the assessed countries regarding the control of the COVID-19 pandemic. The study was divided into two stages. In the first stage, they assessed the relative performance of countries in preventing the outbreak of the disease. In the second stage, they evaluated in the countries' performance on reducing the negative impact of the pandemic on the health status of the general population (i.e. the efficiency of medical treatment) in terms of the total number of confirmed cases, the death cases, and the recovered cases. The respective average efficiency scores from the contagion control and medical treatment efficiency analyses were used to create four quadrants to evaluate the relative efficiency performance for each assessed country. The results showed that while Belgium, Singapore and Vietnam performed efficiently well in both contagion control and medical treatment and thus can serve as benchmarks, China, Italy, and Iraq performed poorly in both aspects, an indication for a swift response to strengthen their health systems.

On the other hand, Breitenbach et al. (2020) examined the efficiency performance of health systems in flattening the contagion curve in the first 100 days after the outbreak of the COVID-19 disease. They employed the non-parametric method of data envelopment analysis (DEA) to assess 31 countries with the most COVID-19 confirmed cases. The number of spared days, which was calculated as the 100 days minus the number of days of persistent infections, as the only output variable. The input variables used in the study include: number of days to lockdown, doctors per thousand population, total COVID-19 tests per one million population, and health expenditure as the percentage of GDP. The results of the study showed that while 12 of the assessed countries were efficient 19 were inefficient in their use of resources to flatten the contagion curve. Germany, Canada, USA, and Austria were among the countries that were found to be inefficient.

Both studies were conducted just in the early few months of the outbreak of the COVID-19 pandemic when most countries were at early stages of the viral infections. These two studies, therefore, are limited in scope in terms of examining the disease trajectories of the virus and its associated responses by various health systems. A lot has changed after these two studies were conducted.

No study has been carried out in the setting of SSA, a region predominantly characterized by precarious health systems, widespread inadequate supply of health resources, and frequent outbreak of pandemics and epidemics such as Ebola, yellow fever, cholera, HIV-AIDS, and dengue fever (Mboussou et al., 2019). Even though the SSA is prone to outbreak of epidemics and pandemics, to the best of my knowledge, no research has been conducted to evaluate the efficiency with which mobilized resources are used to curb their spread. The study intends to assess the efficiency of health systems in SSA in fighting an outbreak of an epidemic or pandemic using the COVID-19 pandemic as a case study. This study is motivated to fill these gaps in the literature, making significant and original contribution by estimating the levels of efficiency in the fight against COVID-19 and identifying the sources of the inefficiencies in the SSA setting.

2. Methodology

2.1 Conceptual Framework

In order to address the objectives of this study, three models were employed to assess the efficiency of healthcare resources spent on curbing the COVID-19 pandemic as depicted in Figure 1. Each of the three models included different input and output variables to distinguish between a production function that consisted of inputs that are mostly geared towards COVID-19 preventive and preparedness of public health measures (Model 1), a production function that incorporates inputs typically based on flattening the COVID-19 contagion curve (Model 2), and a production function that comprises mainly of inputs aimed at medical treatment of COVID-19 patients (Model 3). Table 1 presents the definitions and data sources of the input and output variables included in health production functions.

Model	**Level of Health System Efficiency**	**Inputs**		**Outputs**
Model 1	Efficiency of Public Health Services	• Average of 13 HRCC Index •NPIs Stringency Index	Health Production Function	• Cases per 1M Pop.
Model 2	Efficiency of Flattening the COVID-19 Curve	•Health Spending % GDP •Total Tests/1M Population •NPIs Stringency Index	Health Production Function	•Number of Days to Flatten the curve
Model 3	Efficiency of Medical Treatment Services	•Physicians Density •Inpatient Beds Density •Total Tests/1M Population •NPIs Stringency Index	Health Production Function	•Case Survival Rate •Recovered Cases

Figure 1. The DEA Models of COVID-19 Health Production

This study adopted the two-stage approach, the efficiency indices were first estimated using the health production function (i.e. Efficiency of Healthcare Systems) and then analysis of the effect of health systems' environmental variables on the efficiency indices was undertaken (i.e. Determinants of Health System Efficiency). Thus, the datasets used for this study comprises two different sets of variables. The first set of variables considered were those underlying the health production functions that were used for the estimation of the efficiency indices. The second set of variables consisted of health system characteristics which are outside the purview of the managers of the health systems and healthcare policies that are somehow under the control of policy-makers and influence the functioning of the health production process across SSA countries.

2.2 Data Envelopment Analysis

Two major techniques are widely used in measuring healthcare system performance, namely the stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The DEA approach is particularly useful in measuring efficiency performance of non-profit oriented public organizations such as public healthcare facilities and public utilities. Thus, the use of the DEA approach dominates in literature with regard to measuring efficiency performance of healthcare systems (Hollingsworth & Peacock, 2009). The main advantage of DEA approach is that it can accommodate multiple inputs and multiple outputs measured in different units (Charnes et al., 1994). It is also capable of including exogenously determined environmental variables to explain the differences in the efficiency scores (Banker & Morey, 1994). The DEA model defines efficiency as the ratio of the weighted sum of outputs to the weighted sum of inputs (Mozaffari et al., 2022), which allows for the comparison of performance among countries as to how well each country converts inputs into outputs. Inefficiency is then measured as the ratio of actual to ‘optimum’ performance. The fundamental concept underpinning the DEA approach is the production function. It uses non-parametric technique of linear programming to estimate production frontiers without making any a priori assumptions about the functional form of the related production technology. Today, the scope of the use of DEA models has expanded beyond efficiency measurement to many applications in benchmarking and generating indices as have been reported in the literature (Emrouznejad et al., 2008).

This study followed the DEA approach initially developed by Farrell (1957) and later improved by Charnes, Cooper, and Rhodes (called CCR model) in 1978. The CCR model was further enhanced by Banker, Charnes, and Cooper (called BCC model) in 1984. The CCR model assumes that production has a constant return to scale (CCR), denoting that any change in the input results in a proportionate change in the output.

Table 1. Definition and Sources of Data of Variables used in the DEA Models

Variable	Definition	Data Source
Input Variables		
IHRCC Index	Average of 13 IHRCC scores: Legislation and financing, IHR Coordination and National Focal Point Functions, Zoonotic events and the Human-Animal Health Interface, Food safety, Laboratory, Surveillance, Human resources, National Health Emergency Framework, Health Service Provision, Risk communication, Points of entry, Chemical events, and Radiation emergencies (see Appendix A).	WHO-GHO (2019)
NPIs Stringency Index	Average of nine indicators of the governments’ NPIs: school closure, stay at home restrictions, cancelling of public events, restrictions on gathering size, public transport closure, workplace closure, internal movement restrictions, international movement restrictions, and public information campaigns.	Oxford COVID-19 Government Response Tracker (2020)
Testing intensity	Total cumulative number of COVID-19 virus laboratory tests divided by the total population of the country multiplied by one million.	WHO (2021)
Healthcare Spending	Percentage of Gross Domestic Product spent on healthcare services.	WHO-GHO (2019)
Physicians’ Density	The number of physicians who are actively practicing medicine in public and private institutions (full-time equivalents) per 1,000 population.	WHO-GHO (2019)
Hospital Bed Density	The number of available beds in all public and private inpatient health institutions per 1,000 population.	WHO-GHO (2019)
Output Variables		
Positivity Rate	The ratio of the total confirmed positive COVID-19 cases to the total number of COVID-19 tests times 100. This was transformed into COVID-19 negativity rate.	JHU COVID-19 Data Hub
Number of Days to Flatten COVID-19 curve	The number days, counting from the day the first infection was confirmed to the day when the COVID-19 infection rate started to fall steadily, showing that infections were markedly declining. That is, the inflection point on the COVID-19 trajectory curve (see Appendix E).	Author’s Own Computation
COVID-19 Case Fatality Rate	The ratio of total confirmed deaths to total confirmed cases times 100. It was transformed into case survival rate (CSR).	JHU COVID-19 Data Hub
Recovered Cases	Cumulative number of COVID-19 infected persons who have recovered per 1000 confirmed cases.	JHU COVID-19 Data Hub

NPIs = Non-pharmaceutical interventions.

However, the BCC model assumes a variable return to scale (VRS) in production, meaning a change in input results in either an increase or a decrease in output. The ratio of the technical efficiency scores from the CCR model to the BCC model represents scale efficiency (Cooper, Seiford, & Tone, 2007). This study adopted VRS approach since the output variables (such as recovered COVID-19 cases) may not change proportionately with changes in the input variables (such as NPIs Stringency Index). Again, as explained in the literature (Hollingsworth & Smith, 2003; Olesen et al., 2015) the CCR formulation of DEA should not be used when the dataset include ratio rather than absolute numbers as input and/or output variables since the estimation of the efficiency scores is affected. According to Hollingsworth and Smith (2003), if it becomes necessary to use ratio variables in order to reflect accurately the underlying production function and due to the nature of the available data (as in the case of this study), the BCC formulation of DEA should be used as it is verified to handle such data well.

DEA models have different orientations including input-minimization and output-maximization (Aristovnik, 2012; Martic et al., 2009). The former minimizes inputs while maintaining the prevailing levels of outputs and the latter maximizes output while maintaining the current levels of inputs. This paper used the DEA output-maximization orientation because on the SSA region, the need for healthcare services are poorly met (Fullman et al., 2018), thus, it would be unethical to reduce the amount of healthcare services provided to achieve efficiency goal (Hernández & Sebastián, 2014). Again, the use of output-oriented model is justified in healthcare due to limited control of the managers of the healthcare system over inputs. In most countries in SSA, major decisions regarding investment and recruitment into the health sector are mostly taken by political government departments (Cheng et al., 2016). The study adopted VRS approach with output-maximization orientation DEA model to measure technical efficiency of health systems. Thus, assuming there are $\boldsymbol{s}$ inputs and $\boldsymbol{m}$ outputs for $\boldsymbol{n}$ DMUs (health systems). Let $\boldsymbol{y_j}$ represents the vector of outputs, $\boldsymbol{x_j}$ the vector of the inputs, $\boldsymbol{X}$ is the $(\boldsymbol{s} \times \boldsymbol{n})$ input matrix, and $\boldsymbol{Y}$ is the $(\boldsymbol{m} \times \boldsymbol{n})$ output matrix. Then the standard VRS output-oriented DEA is specified as:

$Max_{\theta,\lambda}\, \theta_j$

$Subject\ to\ the\ constraints$:

$$\theta_j y_j < Y\lambda$$
$$x_j > X\lambda \tag{1}$$
$$n1'\lambda = 1$$
$$\lambda \geq 0$$

where θ_j is a scalar that satisfies $\theta_i \geq 1$ and $\theta_j - 1$ measures the proportional output expansions which can be attained by the j^{th} health system; and λ is a $(\boldsymbol{n} \times \boldsymbol{1})$ vector of constant that measures the weights used to compute the location of an inefficient health system if it were to become efficient**.**

2.3 Second-Stage Analysis: Determinants of Health System Efficiency

The two-stage DEA is being used to investigate factors such as health-system characteristics and healthcare policies that are associated with the technical efficiency scores estimated at the first stage in the previous section. These factors (including NPIs) are usually under the control of health-policy decision makers but not under the control of decision-makers in the health production process such as healthcare providers and patients (de Cos and Moral-Benito, 2014). In most of the DEA literature, Tobit regression is usually employed to account for the effects of these factors (often referred to as environmental variables) on the technical efficiency. This is done by regressing the technical efficiency scores estimated at the first stage against a set of environmental variables as follows:

$$\theta_j = \beta z_j + \varepsilon_j \tag{2}$$

where θ_j is the technical efficiency score, z_j is the vector of environmental variables that affect the technical efficiency health system, β is a vector of the parameters to be estimated, and ε_j is the error term which is assumed to be identical, independently and truncated normally distributed with constant variance σ and zero mean.

This analysis plays a crucial role in providing useful information on available alternatives to improve efficiency performance of health systems. However, Simar and Wilson (2007) argued that such conventional statistical inferences are inappropriate since the first-stage DEA scores and the environmental variables in the second-stage are highly dependent on each other and hence would violate the basic assumptions of regression analysis. Therefore, Simar and Wilson (2007) recommended the use of bootstrap DEA methods. This study employed the bootstrap DEA model to investigate the determinants of health system performance in curbing COVID-19 pandemic. Algorithm #2 suggested by Simar and Wilson (2007) is used in this study (see Appendix F for the details). For more details on the bootstrap DEA methodology in healthcare studies see Simar and Wilson (2007; 2018).

2.4 The Output Variables

The COVID-19 pandemic has acted like a litmus test on the capacity and designs of health systems across the globe. There have been similar pandemics in the recent past – Lassa fever, Ebola virus disease, SARS, Zika virus, and H1N1 – and the threat of more frequent future pandemics is real due to increase in international and domestic travel and trade that makes for a very rapid international spread of any highly infectious virus (Sundararaman et al., 2020). It is, therefore, important to learn the right lessons with regard to building a resilient healthcare systems capable of preventing or resisting health emergency shocks by learning from the current COVID-19 experience. Kruk et al. (2015) defined Health systems resilience as "the capacity of health actors, institutions, and populations to prepare for and effectively respond to crises; maintain core functions when a crisis hits; and, informed by lessons learned during the crisis, reorganize if conditions require it". Response to a crisis needs "both a vigorous public health response and a highly proactive and functioning health-care delivery system" (Kruk et al. 2015). Both these systems must work in concert during a crisis—and indeed they can do so only if designed such long before crisis strikes—which is the element of health systems preparedness. For this reason, *Model 1* was designed to assess the health systems' efficiency in terms of how resources were utilized to enhance the resilience of health systems during pandemics. Thus, for Model 1, we are interested in data relating to delaying or preventing the outbreak and curbing the rapid spread of the COVID-19 virus, i.e. how resilient the countries are able to resist this global pandemic. Therefore, we selected one output variable – COVID-19 positivity rate. Positivity rate is the ratio of the total confirmed positive COVID-19 cases to the total number of COVID-19 tests times 100. Again, we make an assumption that a country with a lower positivity rate has a strong health system to protect its citizens during pandemics. We needed to transform this variable to meet DEA assumptions. The DEA techniques require that output variables are measured in such a way that "more is better". Since the COVID-19 positivity rate (CPR) does not meet this requirement, we computed COVID-19 negativity rate (CNR) as follows:

$$CNR = \frac{1}{CPR} \times 100.$$

The several non-pharmaceutical interventions (NPIs) to flatten the COVID-19 curve have been discussed in the literature (Block et al., 2020; Arshed et al., 2020; and Breitenbach et al., 2020). This approach may not totally eradicate the COVID-19 disease, but it will potentially reduce the stress on health systems (Giesecke, 2020; World Health Organisation, 2020a). A considerable amount of resources and policy interventions including economic lockdowns have been instituted across the globe to achieve the goal of flattening the curve (Koh, 2020; Sharma, Talan, and Jain, 2020; Arshed, 2020). Many countries have struggled in different ways to flatten the curve, but different results emanate. *Model 2* of this paper aims at measuring the efficiency of health systems in flattening the COVID-19 trajectory curve during the first wave of infections. In this regard, we are interested in data relating to the speed at which the curve was flattened, that is, how quickly countries were able to reduce the rate of infections. Thus, the paper adopted an output variable which is computed as the difference between the date when the first case was detected to the date when the COVID-19 infections started to fall steadily, showing that infections were markedly declining. In order to avoid misspecification of the model and ensure that countries that flatten their curves earlier are not represented by low values, this output variable was inverted (see Breitenbach et al., 2020; Arshed et al., 2020; Appendix E for COVID-19 epidemiological curves).

The COVID-19 pandemic has been characterized by significant morbidity and mortality of varying degrees across countries. Medical treatments have been administered to COVID-19 patients in order to control the viral infection. Medical resources such as medical personnel, inpatient hospital beds, ventilators, and others have come under intense usage since the outbreak of the pandemic. Different medical treatment measures have been taken by each country with differing outcomes. In this paper, *Model 3* seeks to compare the relative performance of each sampled country as to whether the resources used in treating COVID-19 patients are being used efficiently or not. In order to empirically carry out this assessment, two output variables were selected – case fatality rate and recovered cases per 1000 confirmed cases. The COVID-19 case fatality rate (CFR), which is measured as the ratio of total confirmed deaths to total confirmed cases times 100, was transformed into case survival rate (CSR) to meet DEA model requirement of 'more is better' as follows:

$$CSR = \frac{1}{CFR} \times 100.$$

2.5 Input Variables

The input variables used in the production function of this paper included physicians' density, inpatient beds density, health spending as a proportion of GDP, and the average of 13 International Health Core Capacity Scores

(IHRCCS). These input variables are widely used in studies of health production efficiency (Breitenbach et al., 2020; Shirouyehzad et al., 2020; See and Yen, 2018; Ambapour, 2015; Sinimole, 2012; Spinks and Hollingsworth, 2009). The average of the IHRCCS is used to reflect the resilience, emergency preparedness capacity against health threat, and the overall public health of national health systems (Sundararaman et al., 2020). The 13 core capacities are: (1) Legislation and financing; (2) IHR Coordination and National Focal Point Functions; (3) Zoonotic events and the Human-Animal Health Interface; (4) Food safety; (5) Laboratory; (6) Surveillance; (7) Human resources; (8) National Health Emergency Framework; (9) Health Service Provision; (10) Risk communication; (11) Points of entry; (12) Chemical events; (13) Radiation emergencies (World Health Organization, 2005). They are all measured on the scale between 0 (minimum score) and 100 (maximum score). Appendix A details the scores for each capacity for all the sampled countries plus the definitions of all the capacities.

Since this paper analyzes the efficiency of health systems in combating the COVID-19 pandemic, we chose two inputs that are unique to COVID-19 for the three models: total COVID-19 tests per one million population and non-pharmaceutical interventions (NPIs) stringency index (SI). The total COVID-19 tests per one million population was used to reflect the level of resources, both human and material, that have been spent in the fight against the spread of the virus (Arshed et al., 2020). On the other hand, the stringency index (SI) is a composite index of nine indicators that captures variations in governments' COVID-19 NPIs to contain the spread of the virus and augment health systems (Hale et al., 2020). The nine indicators of the NPIs are: (1) school closure; (2) stay at home restrictions; (3) cancelling of public events; (4) restrictions on gathering size; (5) public transport closure; (6) workplace closure; (7) internal movement restrictions; (8) international movement restrictions; and (9) public information campaigns. Each of the nine indicators were rescaled to a value from 0 to 100 (100 = strictest). Then the nine scores were averaged to get the composite Stringency Index (For more details on the construction of the NPIs Stringency Index see Appendix B). Table 1 presents the definitions and the sources of data used in the three DEA models.

2.6 Explanatory Variables

In order to investigate the effect of health systems characteristics and healthcare policies on health systems efficiency, we selected some explanatory variables which are defined in Table 2. Based on literature seven explanatory variables were selected as determinants of health system efficiency: (1) governance indicator variable (the average of World Bank's six governance quality indicators); (2) level of economic activities variable (GDP per capita); (3) tobacco use prevalence; (4) proportion of population aged 65 years and above; (5) population density; (6) average temperature levels; and a categorical variable of income groupings of the studied countries (see Wang, Rodrigues, and Barmejo, 2020; Arshed, Meo, and Farooq, 2020; Ahmed, Hassan, MacLennan, et al., 2020; Hadad, Hadad, & Simon-Tuval, 2013).

2.6.1 Governance Quality

World Bank's Worldwide Governance Indicators (WGI) are a research dataset summarizing views on the quality of governance in both industrial and developing countries. These indicators which have been published since 1996 covers six dimensions of governance: control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and absence of violence. This variable is included in the second-stage analysis to assess the impact of the quality of governance in health systems performance in curbing the COVID-19 pandemic. A plethora of empirical evidence indicate a positive correlation between health system performance and quality of governance (Ibrahim et al., 2018; Wranik, 2012). The quality of governance was measured as the average of all the six dimensions from 2016 to 2018. This variable is adopted in Model 3.

2.6.2 Size of Economy

GDP per capita vary markedly across the SSA countries. One empirical study by Mo et al. (2020) found an evidence of a positive relationship between GDP and the spread of COVID-19 virus. A low GDP per capita implies low economic activities and less human interactions. Hence, it is not surprising that territories with higher GPD may appear to have higher COVID-19 cumulative cases. This variable is employed in all the three models.

2.6.3 Tobacco Use Prevalence

Tobacco use prevalence was employed as a proxy of the population's lifestyle and behavior which can impact the severity of the spread of the COVID-19 virus. According to Guan et al. (2020), people who smoke have 3.25 higher odds of developing severe forms of COVID-19 disease as compared to non-smokers. Accumulating evidence indicates that tobacco use affects health outcomes and also the health system efficiency (Allin, Grignon, and Wang, 2016; Afonso and St. Aubyn, 2011; Johansson and Sundquist, 1999). Tobacco use prevalence was measured as the proportion of the population aged 15 years and above who regularly smoke. This variable is employed in all the three models.

2.6.4 Aged Population

Another social environmental variable in the models of this paper is the aged population, which provides a measure of age-related risk of severe COVID-19 disease. COVID-19 is often more severe in the people advanced in years or with underlying health conditions like lung or heart diseases, diabetes, or conditions that affect their immune system (Novosad et al., 2020; Ghisolfi et al., 2020; Okeahalam et al., 2020). Holts et al., (2020) provides a strong evidence of age-related gradient for risk of severe COVID-19 disease, hospitalization and deaths. The aged population was measured as the proportion of the population aged 65 years and above.

2.6.5 Population Density

Evidence from several empirical studies shows that population density has a significant effect on health system performance (Ahmed et al., 2019; See and Yen, 2018; Greene, 2010; and Kumbhakar, 2010). In this study, we postulate that a health system with a lower population density would have significant positive impact on health system efficiency in the midst of the COVID-19 pandemic due to its implications for social distancing and quality of healthcare services. This variable is measured as the size of the average population living on a kilometer of land area.

2.6.6 Temperature Levels

The relationship between temperature levels and the spread of COVID-19 virus is well documented in the literature (Aidoo et al., 2021; Roy, 2020; Kassem, 2020; Corripio and Raso 2020; Wang, Rodrigues, and Barmejo, 2020). The consensus among these studies is that there is an inverse relationship between the spread of COVID-19 virus and temperature. For instance, Aidoo et al. (2021) found that the risk of the spread significantly decreases when average temperature exceeds 29^{o}C. Wang, Rodrigues, and Barmejo (2020) estimated that every 1°C increase in the minimum temperature leads to a decrease in the cumulative number of cases by 0.86. The average monthly temperature for each country is included in the Model 2.

2.6.7 Level of Economic Development

A categorical variable of three income groupings – low-income, lower-middle-income, and upper-middle-income – of the studied countries was created to examine the influence of their level of development on health system performance in curbing the COVID-19 virus. Table 2 presents the definitions and the sources of variables used in the second-stage analysis.

We also employed the Simar and Wilson (2007) double bootstrap DEA approach to estimate robust bias-corrected efficiency scores from the bootstrapped regression analysis to identify factors associated with these estimated efficiency scores. The *simarwilson* command in STATA Version 15 was used in the analyses.

2.7 Data Sources

Data for the study were obtained from three main sources: the John Hopkins University COVID-19 Data Repository (https://coronavirus.jhu.edu), Worldometer COVID-19 Data Repository (https://worldometer.info), and COVID-19 Data Hub developed by Guidotti and Ardia (2020) (https://covid19datahub.io). COVID-19 indicators of confirmed, recovered, death cases and other quantitative related data were sourced from databases of John Hopkins University and Worldometer COVID-19 databases. However, qualitative indicators on government policy interventions data were sourced from COVID-19 Data Hub developed by Guidotti and Ardia (2020). Due to wide fluctuations in the daily trends of confirmed, recovered, and death cases as a result of irregular intervals of reporting, the study used 21-day moving averages of reported cases in order to better appreciate the trends.

This is a cross-sectional study using data on 46 countries in SSA. These countries were selected based on the fact that the relevant COVID-19 data required for the study's analyses were regularly reported on during the study period, which was between December 29, 2019 and February 28, 2021. According to the list provided by United Nations Statistics Division, there are 50 Sub-Saharan African countries and territories. Six countries and territories (i.e. Tanzania, Sudan, South Sudan, Djibouti, Eritrea, Reunion, and Mayotte) were excluded from the study due to missing data of some selected relevant variables in the databases.

Table 2. Definitions and Sources of Variables used in Second-Stage of Efficiency Analysis

Variable	**Definition**	**Data Source**
Average governance quality	Average of six governance quality indicators: control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and absence of violence.	WB-WGI
GDP per capita	Gross Domestic Product (GDP) per capita converted to international dollars using purchasing power parity (PPP) rates.	WB-WDI
Tobacco Use Prevalence	The proportion of the population aged 15 years and above who regularly smoke.	WB-WDI
Aged population	The proportion of the population who are aged 65 years and above.	WB-WDI
Population Density	The size of the average population living on a kilometer of land area.	WB-WDI
Temperature (^{o}C)	The average of 12 months temperature measured in degree Celsius.	WB-WDI

3. Empirical Results and Discussion

3.1 Descriptive Statistics

Table 3 presents the descriptive statistics for the input and output variables used in the study for the efficiency estimations. The performance of health systems in the SSA region in their fight against the spread of the COVID-19 virus was estimated based on six inputs and five outputs in three models - COVID-19 contagion control model, flattening the COVID-19 contagion curve model, and medical treatment model.. A total of 44 SSA countries (representing nearly 90% of all SSA countries) were used in this study based on the availability of relevant data required for the efficiency analysis.

Table 3. Descriptive Statistics of COVID-19 healthcare inputs and outputs used in the models

Indicator	Mean	Minimum		Maximum	
		Value	Country	Value	Country
Inputs:					
Total tests per 1M Population	46,866	1,117	Congo, DR	281,082	Botswana
NPIs Stringency Index	47.2	12.5	Burundi	70.2	Eritrea
HRCC Index (SPAR)	43.9	17.0	CAR	71.0	Rwanda
Health expenditure (% GDP)	5.67	2.65	Djibouti	17.41	Sierra Leone
Physicians’ density	0.22	0.02	Niger	2.00	Mauritius
Inpatient bed density	1.36	0.20	Senegal	4.40	Seychelles
Outputs:					
Total cases per 1M Population	4,284	171	Burundi	27,077	Cabo Verde
Days to flatten the curve	244.5	23	Mauritius	355	Benin*
Case fatality rate	1.84	0.10	Burundi	4.20	Mali
Recovery rate	82.8	34.2	Lesotho	98.3	CAR

*As at the end of the cut-off date (February 28, 2021) used in this paper, 4 countries (i.e. Benin, Gabon, Seychelles, and Togo) had not been able to flatten their COVID-19 contagion curve.

As indicated on the Table 3, an average number of COVID-19 total laboratory tests per one million population is 46,866 and an average non-pharmaceutical interventions (NPIs) Stringency Index and the HRCC Index are 47.2 and 43.9, respectively. The average health expenditure as a proportion of GDP is 5.67%. The average number of physicians per thousand population is 0.22, while the average number of inpatient beds per thousand population is recorded as 1.36, with a maximum value of 4.20 (in Seychelles) and a minimum value of 0.20 (in Senegal).

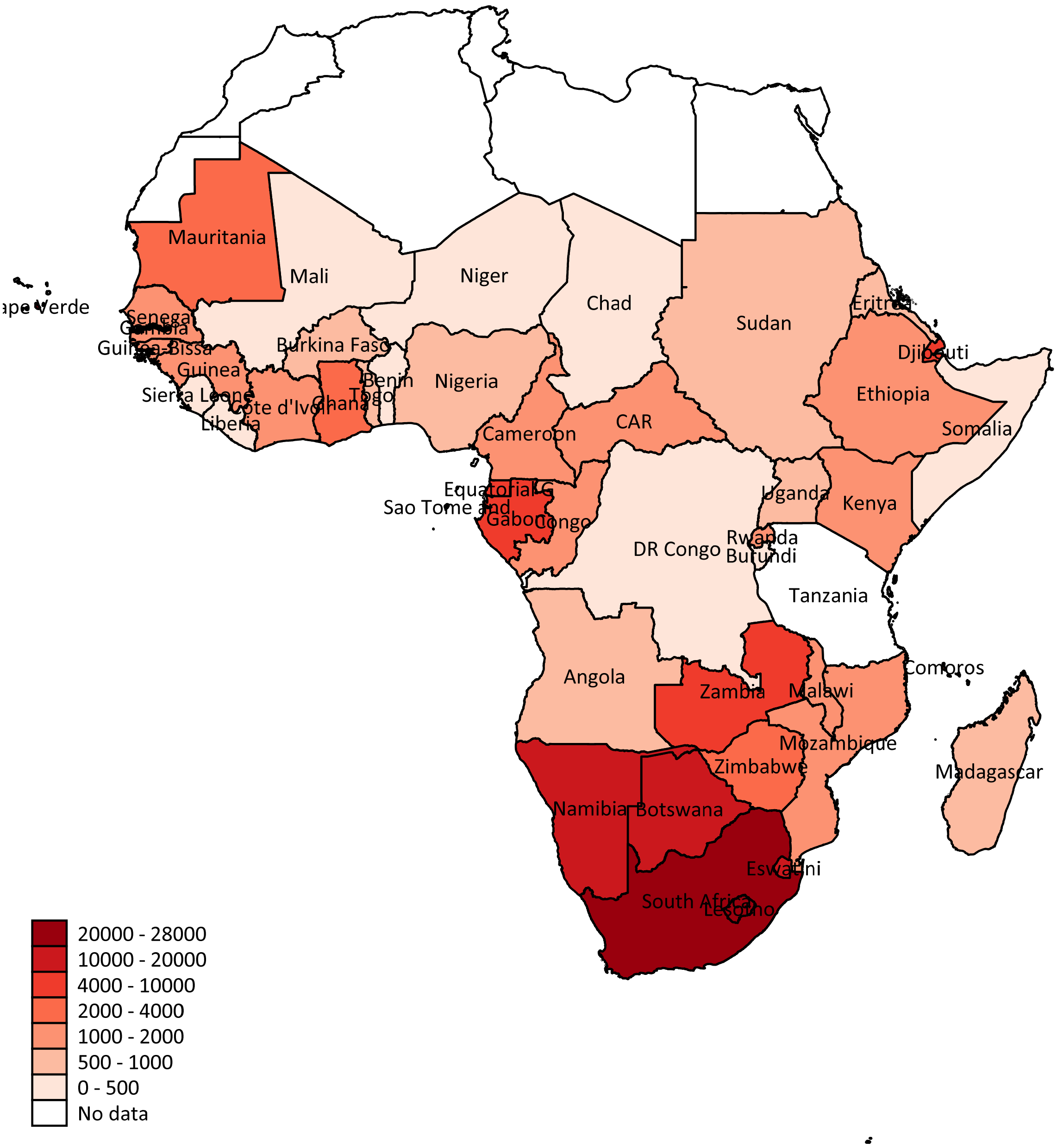

Figure 2. Choropleth map showing incidence of COVID-19 cases per one million population

For the output measures, total number of COVID-19 cases per one million population is averaged at 4,282 across the region. It took an average of 79 days for countries in the SSA region to record their first cases of COVID-19 virus after its emergence in the city of Wuhan, Hubei Province in the People's Republic of China (Newey and Gulland, 2020), on December 29, 2019. An average of 245 days were used by the 44 sampled SSA countries to flattening the COVID-19 contagion curve with a minimum of 23 days (in Mauritius) and a maximum of 355 days (in Senegal). There were four countries (i.e. Benin, Gabon, Seychelles, and Togo) which had not been able to flatten the curve at the end of the cut-off date (February 28, 2021) for this study. The average case fatality rate is 1.84%, while an average recovery rate of 82.8% is recorded in the region.

Figure 2 plots the COVID-19 cases per one million population on the map. It can be observed here that countries like South Africa, Seychelles, and Lesotho have greater values. They are followed by countries like Namibia, Botswana, Gabon, Ethiopia, Ghana, Rwanda Eswatini, and Zambia.

Figure 3 shows a quick scatter plot relating the number of COVID-19 cases per one million population and the NPIs Stringency Index. A quick inspection of the plot reveals that there is a negative correlation, that is, the stricter governments' interventions are generally associated with lower COVID-19 cases.

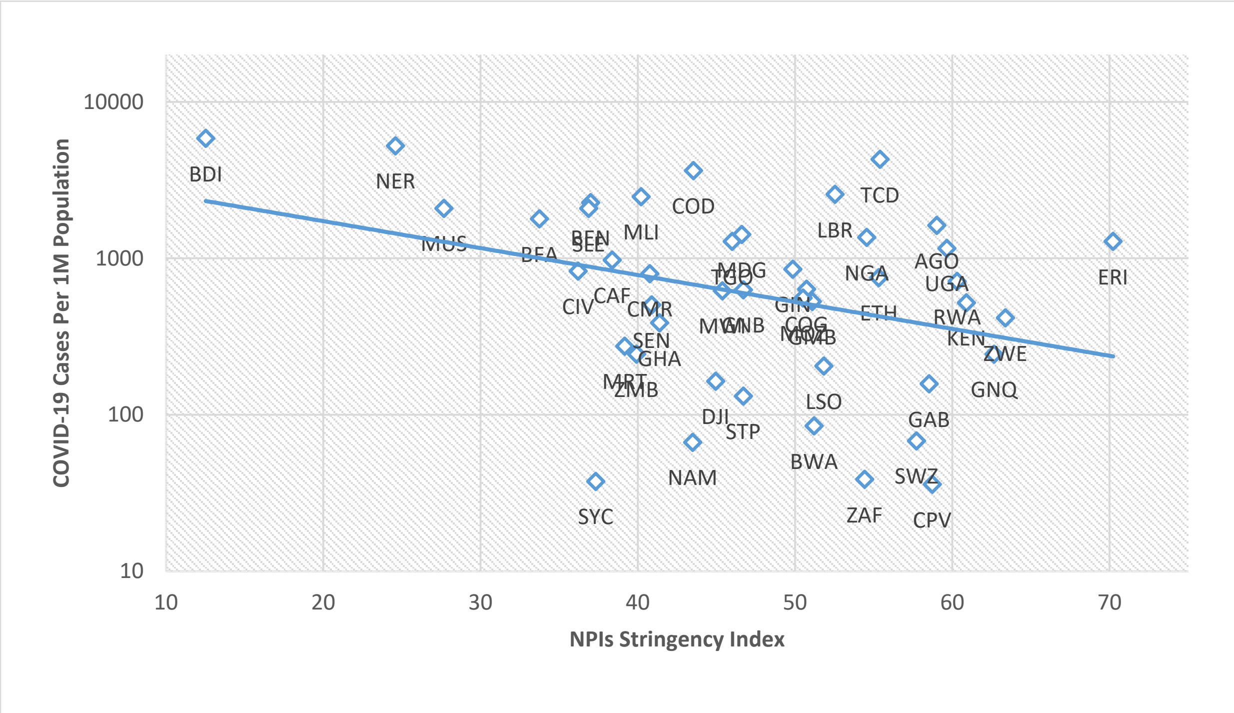

Figure 3. NPIs Stringency Index and COVID-19 Cases per 1 Million Population

3.2 First-stage DEA Results: Efficiency Scores, Rankings, and Classifications of Countries

The efficiency scores for all the selected SSA countries' health systems in this study were computed using STATA packages of *teradial* and *simarwilson*. The results of the original DEA scores, bootstrap bias estimates and Farrell bias-corrected output-oriented efficiency scores under VRS, which range from one to infinity, are presented at Appendix C. For easy reading and analysis, the Farrell bias-corrected efficiency scores were converted into Shepherd bias-corrected efficiency scores, which range from zero to one, are ranked and presented in Table 1.4 for each of the three models in this study.

In the given sample of 44 SSA countries, 20 countries are classified as low-income, 17 countries as middle-lower-income, and 7 countries as upper-middle-income or high-income (World Bank, 2020). Based on the proposed methodology, in the first stage of this study, the efficiency of public health measures instituted by the various health systems in the SSA countries to curb the spread of contagious diseases in general and COVID-19 virus in particular were evaluated. In this stage, the average of the 13 IHRCCs, NPIs Stringency Index, and the number of COVID-19 tests per one million population were used as input variables whilst spared days and COVID-19 cases per one million population were used as output variables. The results for the three income groups are presented in Figure 4.

Table 4. Shepherd Output-Oriented Bias-Corrected Efficiency Scores under VRS and Ranks

Country	Efficiency Score of COVID-19 Public Health	Rank	Efficiency Score Flattening the COVID-19 Curve	Rank	Efficiency Score of COVID-19 Medical Treatment	Rank
Angola	0.5773	14	0.8459	9	0.9781	37
Burundi	0.7236	5	0.6413	23	0.9909	19
Benin	0.5883	12	0.5591	32	0.9888	25
Burkina Faso	0.4921	25	0.7058	19	0.9824	34
Botswana	0.5200	21	0.4449	39	0.9913	17
Central Africa Rep.	0.8333	1	0.9168	4	0.9959	8
Cote d'Ivoire	0.4873	26	0.8555	8	0.9809	35
Cameroon	0.4277	41	0.7464	17	0.9892	24
Congo, Dem. Rep.	0.6748	6	0.7639	16	0.9825	33
Congo, Rep.	0.4541	38	0.8226	11	0.9860	29
Cabo Verde	0.4751	34	0.7955	13	0.9940	14
Djibouti	0.4736	35	0.5913	26	0.9949	11
Eritrea	0.5586	18	0.6047	25	0.9946	13
Ethiopia	0.4816	30	0.8642	7	0.9963	6
Gabon	0.4492	39	0.0175	44	0.9978	3
Ghana	0.4838	28	0.3251	40	0.9957	10
Guinea	0.4798	31	0.8941	6	0.9949	12
Gambia, The	0.4752	33	0.8396	10	0.9699	40
Guinea-Bissau	0.6173	9	0.9588	1	0.9896	23
Equatorial Guinea	0.5947	11	0.8206	12	0.9867	27
Kenya	0.4592	36	0.7826	14	0.9835	31
Liberia	0.5830	13	0.9464	2	0.9961	7
Lesotho	0.7477	4	0.5602	31	0.9717	38
Madagascar	0.6151	10	0.9079	5	0.9419	44
Mali	0.6348	7	0.6544	22	0.9653	41
Mozambique	0.5206	20	0.4705	38	0.9904	21
Mauritania	0.4794	32	0.6575	21	0.9827	32
Mauritius	0.5726	16	0.7248	18	0.9981	1
Malawi	0.5668	17	0.4977	36	0.9963	5
Namibia	0.4828	29	0.6145	24	0.9921	16
Niger	0.8047	3	0.7710	15	0.9959	9
Nigeria	0.4243	42	0.5278	33	0.9884	26
Rwanda	0.4858	27	0.5000	35	0.9911	18
Senegal	0.4148	43	0.1142	42	0.9965	4
Sierra Leone	0.6263	8	0.4779	37	0.9860	28
Sao Tome & Principe	0.5745	15	0.9296	3	0.9857	30
Eswatini	0.4336	40	0.5725	30	0.9630	42
Seychelles	0.5028	23	0.0189	43	0.9981	2

Chad	0.8165	2	0.5783	29	0.9801	36
Togo	0.4547	37	0.2737	41	0.9908	20
Uganda	0.5527	19	0.7024	20	0.9925	15
South Africa	0.3909	44	0.5856	27	0.9707	39
Zambia	0.5195	22	0.5067	34	0.9899	22
Zimbabwe	0.4974	24	0.5824	28	0.9618	43

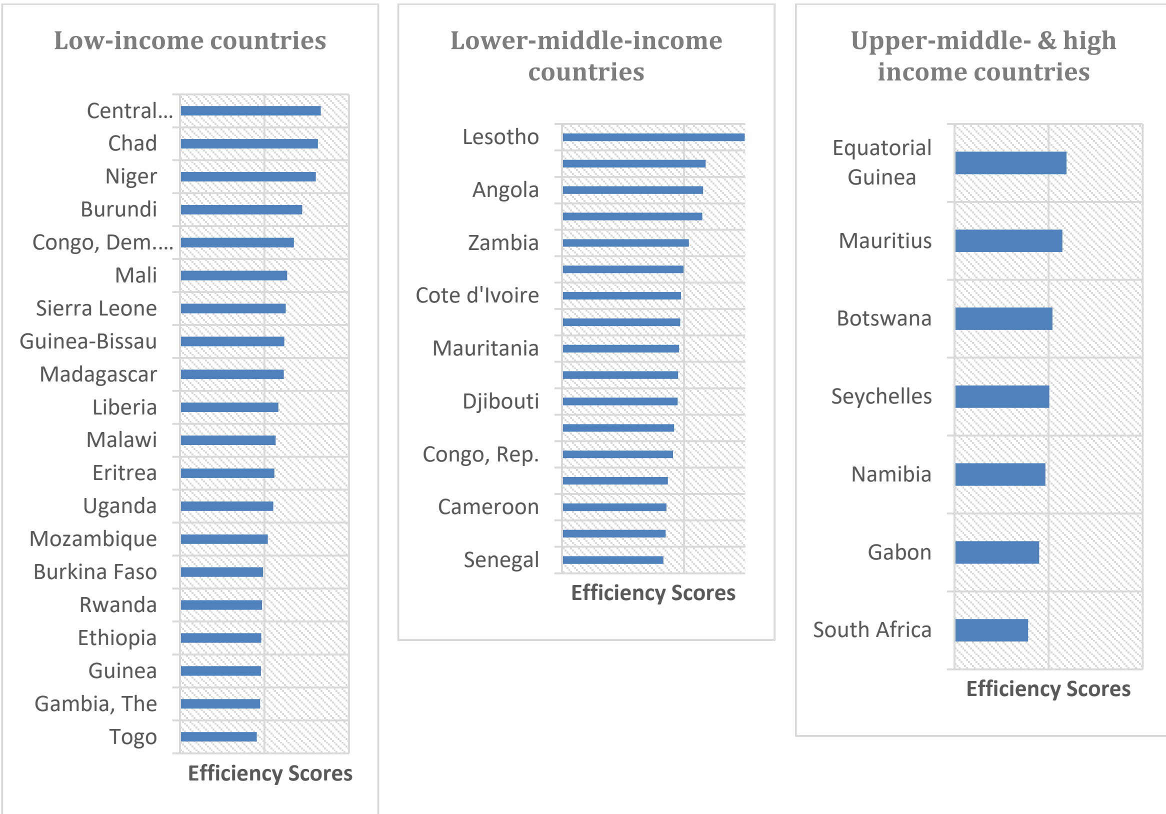

Figure 4. SSA Health Systems Performance: COVID-19 Public Health Measures

The results show that the average efficiency score for the COVID-19 public health division for the low-income countries is 0.60 whereas that of middle-lower-income countries and upper-middle-income countries are 0.51 and 0.50, respectively. From Figure 4, we observe that Central African Republic, Lesotho, and Equatorial Guinea obtained efficiency scores greater than 0.61 and were ranked at the top of the low-income, lower-middle-income, and upper-middle income groups, respectively. Thus, these countries offer useful information for the less efficient countries within the same income groups as they are considered as good references. At the other end of the spectrum, Togo (low-income country), Senegal (middle-income country), and South Africa (upper-middle-income country) had the worst health systems among their respective income groups. The results from the bootstrap DEA framework suggest that with the given capacity and resources, more efficient utilization of their resources could potentially enhance output by 45% in terms of COVID-19 cases per one million population.

In the second model of this study, we examine the efficiency with which health systems in SSA are able to flatten the COVID-19 contagion curve using the NPIs Stringency Index, number of COVID-19 tests per one million population, and healthcare expenditure as a percentage of GDP as input variables and the number of days left in the cycle as the only output variable. The results as presented on Figure 5 show that Guinea-Bissau and Liberia (Low-income countries), Sao Tome & Principe and Cote d'Ivoire (Lower-middle-income countries), and Equatorial Guinea and Mauritius (Upper-middle income countries) are more efficient in comparison to other countries in their respective income groups. Therefore, these countries serve as good peers for the less efficient countries within their respective income groups. The average efficiency score for low-income countries in flattening the curve is 0.70 whereas the middle income and upper-middle income countries registered an average scores of 0.63 and 0.46, respectively.

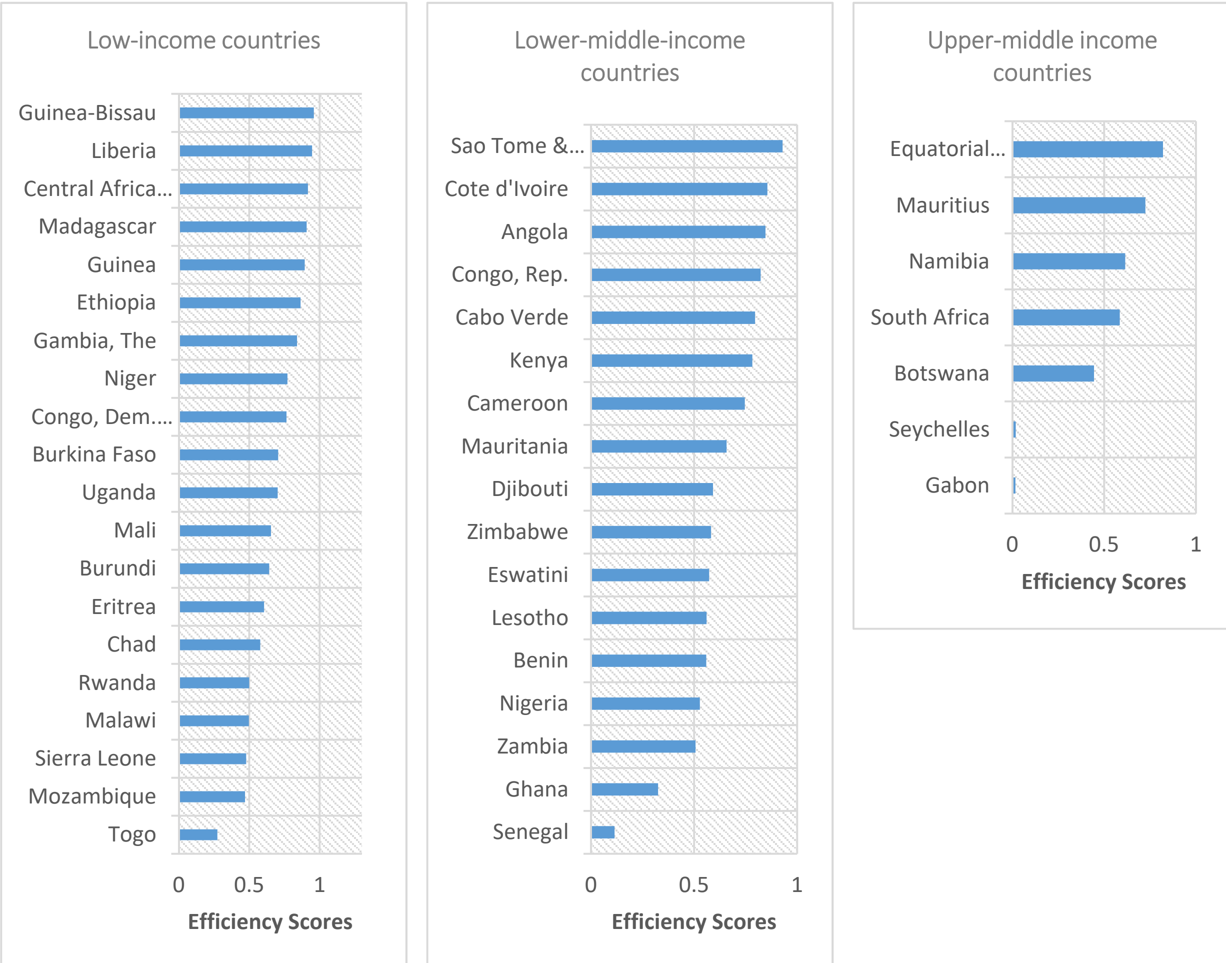

Figure 5. SSA Health Systems' Performance: Flattening the COVID-19 contagion curve

In the third model, based on the proposed methodology, DEA is performed to assess the efficiency performance of health systems in the medical treatment of COVID-19 patients. In this model, NPIs stringency index, number of COVID-19 laboratory tests per one million population, physicians per thousand population, and inpatient beds per thousand population were used as inputs whereas the number of recovered COVID-19 patients per thousand confirmed cases and the inverse of the number of deaths per thousand COVID-19 cases were used as outputs. The results for the 44 studied SSA countries are presented on Figure 6.

The results show that Madagascar (low-income countries), Zimbabwe (lower-middle-income countries), and South Africa (upper-middle-income countries) have had poor performance in the medical treatment of COVID-19 patients in comparison with other countries in their respective income groups in this study. However, countries such as Malawi (low-income countries), Senegal (lower-middle-income countries), and Mauritius (upper-middle-income countries) serve as good role models for the less efficient countries to emulate from in the treatment of COVID-19 patients.

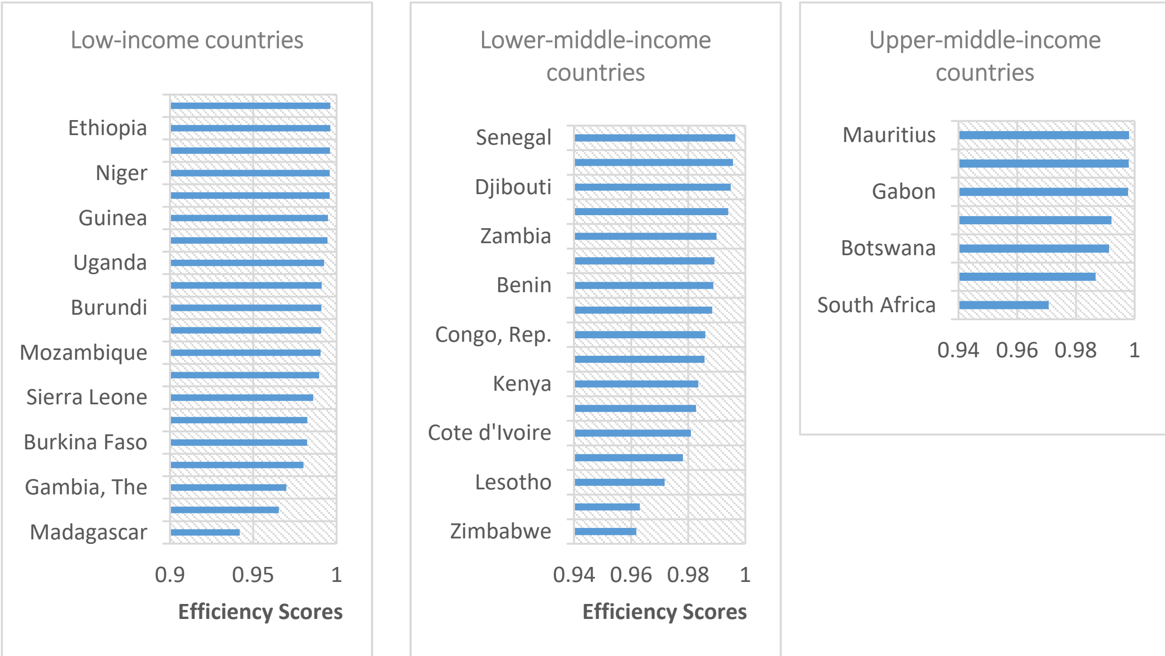

Figure 6. SSA Health Systems Performance: COVID-19 Medical Treatments

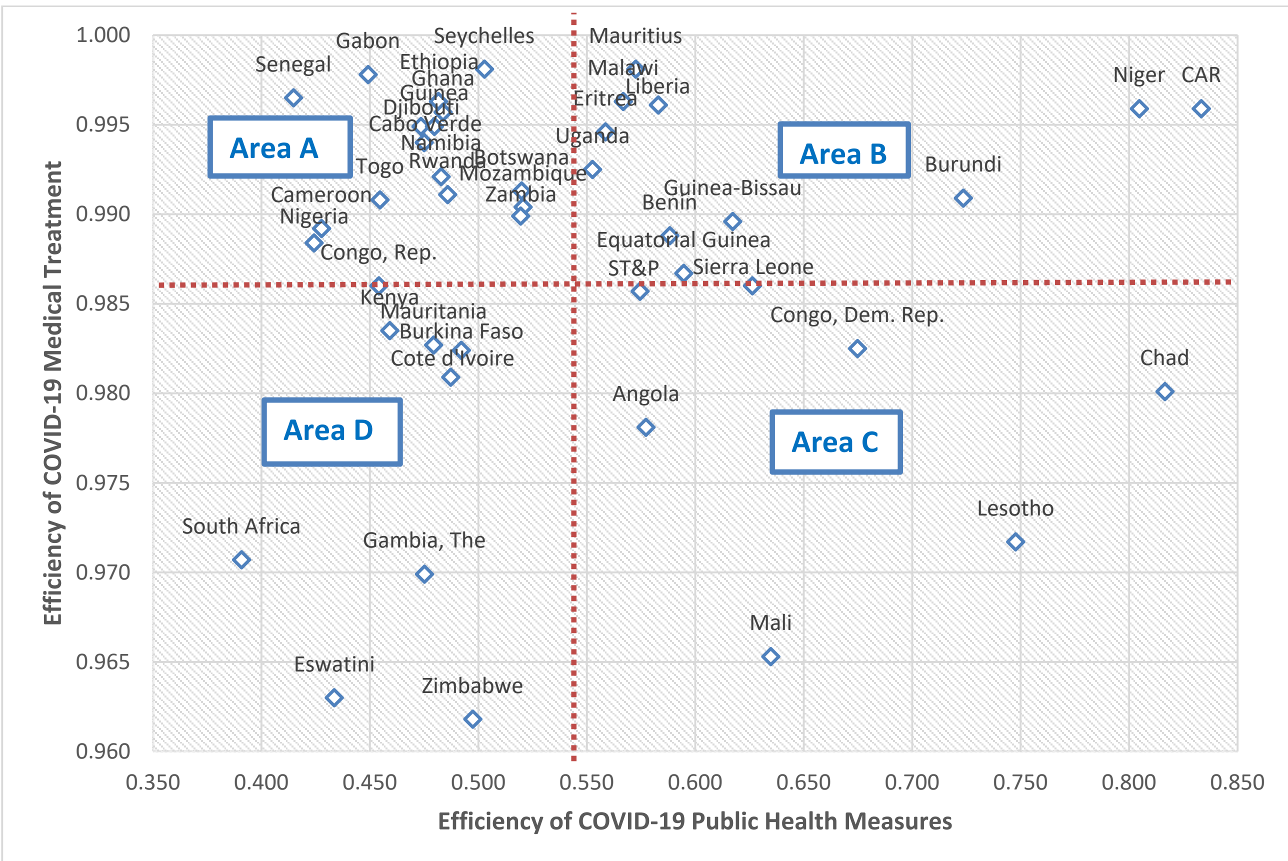

Figure 7. Classification of SSA countries based on COVID-19 efficiency performance

The efficiency scores in the first and the third models of this study (i.e. efficiency of COVID-19 public health measures and efficiency of COVID-19 medical treatments) are used to classify the studied countries by creating a scatter plot. The average efficiency scores for the first and the third models, 0.546 and 0.986, respectively, are used to divide the scatter plot into four areas: A, B, C, and D as shown in Figure 7. From the plot, it can be observed that countries such as Central Africa Republic (CAR), Mauritius, Niger, Malawi, Equatorial Guinea, Burundi, and Eritrea which are in area B of the plot have been efficient in both public health measures and medical treatment of COVID-19 patients, and can serve as benchmarks. Countries in area A of the plot such as Rwanda, Ghana, Senegal, Gabon, and Seychelles have efficiently carried out medical treatment of COVID-19 infected persons but have been poor in implementing public health measures to curb the spread of the virus. These countries can serve as good references regarding medical treatments of COVID-19 patients.

On the other hand, countries in area C of the Figure7 – Lesotho, Mali, Angola, Chad, and, Democratic Republic of Congo – have been more efficient in the implementation of the public health measures aimed at curbing the spread of the COVID-19 virus but poor in the medical treatment of persons infected with the virus. These countries can serve as benchmarks for implementing public health measures to fight the spread of the COVID-19 virus. Countries in area D are those in worst situation with poor performance in both medical treatment and implementation of public health measures. There is an urgent need for these countries to improve their current conditions. The countries in the area D are South Africa, Zimbabwe, Kenya, Mauritania, Eswatini, Gambia, Cote d'Ivoire, and Congo Republic.

3.3 The Results of Second-Stage Bootstrap DEA

The differences in the efficiency scores of the studied SSA countries' health systems computed by bootstrap bias-corrected DEA could be explained by health systems characteristics which were not included in the first-stage DEA. In this study, after careful review of both COVID-19 literature and health systems studies, GDP per capita (GDP), population density (DENSITY), aged population (AGED), average temperature levels (TEMPERATURE), prevalence of tobacco use (TOBACCO), governance quality (GOVERNANCE), and categorical variable of income groups (LOW-INCOME, LOWER-MIDDLE-INCOME, and UPPER-MIDDLE-INCOME countries), using low-income countries as a reference category, were included as explanatory variables in the second-stage of bootstrap DEA framework. Some of the variables are excluded in some of the three models employed in this study due to collinearity problems and insignificant results. Table 5 presents the estimation results from the bootstrap procedures employing algorithm #2 from Simar and Wilson (2007). The regression procedure uses the estimated inefficiencies ($i.e. \theta_m^* > 1$) generated in the first-stage DEA as dependent variable. Thus, a positive coefficient implies that an increase in a relevant explanatory variable is associated with an increase in inefficiency of the countries' health systems.

GDP per capita is included in the analysis to capture the impact of the level of economic activities on the performance of health systems in fighting the COVID-19 pandemic. The relationship between GDP per capita and health system inefficiency is found to be positive for model 1 ($\beta = 0.177, P < 0.01$) and model 3 ($\beta = 0.0254, P < 0.01$). This suggests that higher levels of GDP are associated with poor health system performance in curbing the spread of the disease, particularly in the use of public health measures and medical treatment of COVID-19 infected persons, and portends a conclusion that higher levels of economic growth pose real risk for the spread of infectious diseases. In fact, a simple Spearman correlation test shows that the cumulative cases per one million population were positively correlated with GDP per capita ($r = 0.64, P < 0.01$). This result is consistent with those obtained in an earlier empirical studies, such as Mo et al. (2020), where increases in GDP was found to increase cumulative COVID-19 cases and Hadad, Hadad, and Simon-Tuvel (2013) where increases in GDP per capita was found to decrease health system efficiency.

Empirically, the tobacco use have not had any significant effect on the performance of health systems efficiency as far as COVID-19 public health measures in model 1 and efforts to flatten the contagion curve in model 2 are concerned. However, in terms of medical treatment of COVID-19 patients, the prevalence of tobacco use have had a significant negative impact ($\beta = 0.0027, P < 0.01$) on health systems efficiency. That is, higher levels of tobacco use are associated with health system inefficiency in the medical treatment of COVID-19 patients. This is in line with earlier empirical studies, such as Allin, Grignon, and Wang (2016) and Afonso and St. Aubyn (2011), which found tobacco use to be significantly associated with lower health systems efficiency.

Table 5. Results of second-stage bootstrap truncated regressions

VARIABLES	MODEL 1	MODEL 2	MODEL 3
GDP	0.177**	-5.581	0.0254***
	(0.0691)	(3.901)	(0.00598)
TOBACCO	-0.0022	0.0243	0.00266***
	(0.0040)	(0.172)	(0.000374)
AGED	0.0984	0.507	-0.00809***
	(0.0259)	(0.835)	(0.00242)
GOVERNANCE			-0.0162***
			(0.00471)
TEMPERATURE		1.647**	
		(0.804)	
DENSITY	0.093***	4.754**	-0.00147
	(0.0269)	(2.334)	(0.00231)
2.LOWER-MIDDLE-INCOME	0.4246*	24.05*	-0.0620***
	(0.2186)	(13.80)	(0.0159)
3.UPPER-MIDDLE-INCOME	0.2987	47.88**	-0.0623***
	(0.2278)	(21.88)	(0.0212)
2.INCGROUP#c.DENSITY	-0.1050**	-3.588	0.0116***
	(0.0469)	(2.609)	(0.00346)
3.INCGROUP#c.DENSITY	-0.143***	-5.350*	0.00174
	(0.0488)	(2.887)	(0.00486)
CONSTANT	-1.164**	-35.31	-0.194***
	(0.5153)	(30.42)	(0.0500)
SIGMA	0.135***	2.158***	0.00834***
	(0.0143)	(0.587)	(0.00111)

Notes. Standard errors in parentheses. Dependent variables: inefficiency scores ($i.e. \theta_m^* > 1$). *** p<0.01, ** p<0.05, * p<0.1.

The proportion of aged population is included in the second-stage analysis to assess the effect of age-related risk of severe COVID-19 disease resulting from underlying health conditions that affect their immune systems on health systems performance. Interestingly, it was not found to be associated with the health system's efficiency according to both models 1 and 2. However, as depicted in Table 5, in model 3, aged population was estimated to be negative ($\beta = -0.0081, P < 0.01$), which indicates that countries with more aged population are more likely to be more efficient in medical treatment of COVID-19 patients. This result contradicts a priori expectation but not surprising considering the youthfulness of populations across many SSA countries with a very negligible proportion of the aged population.

The negative relationship between governance quality and health systems inefficiency, which indicates that well governed countries are more likely to have efficient health systems in medical treatment of COVID-19 patients, coincides with Ibrahim et al. (2018) and Wranik (2012).

Temperature is found to be positively associated with health system inefficiency ($\beta = 1.647, P < 0.05$) in flattening the COVID-19 contagion curve. The implication of this result is that countries with higher levels of temperature are likely to be more efficient in reducing the rate of transmission of the COVID-19 virus. The finding is similar to other earlier empirical studies (Aidoo et al., 2021; Roy, 2020; Kassem, 2020; Corripio and Raso 2020; Wang, Rodrigues, and Barmejo, 2020) all of which found temperature to be negatively associated with the rate of COVID-19 virus infections. The comparatively low COVID-19 cases in the SSA region may be attributed to the higher levels of temperature in the sub-region.

Again, from Table 5, it is observed that among the three categories of countries the low-income countries performance in implementation of COVID-19 public health measures (Model 1) and in flattening the COVID-19 contagion curve (Model 2) is better as compared to lower-middle-income and upper-middle-income countries. However, in terms of medical treatment of COVID-19 patients (Model 3), the performance of lower-middle-income and upper-middle-income countries is significantly better than low-income countries.

Population density is included in the second-stage analysis to investigate the impact of social distancing on health system efficiency in the fight against the spread of COVID-19 virus. The estimated coefficient for the population density variable is positive for both model 1 $(\beta = 0.0925, P < 0.01)$ and model 2 $(\beta = 4{,}754, P < 0.05)$. The results favor the proposition that higher population density does not bode well for social distancing, a public health measure essential in the fight against the spread of the COVID-19 virus. However, the effect differs among the three income groups. The negative impact of population density on efficiency performance is more intense among low-income countries relative to lower-middle-income countries and upper-middle-income countries. These findings are in line with most previous literature (see Kumbhakar, 2010; Greene, 2010; and See and Yen, 2018).

3.4 Sensitivity Analyses and Robustness Checks

In this study, across all the three models employed, the number of DMUs were far in excess of the requirement that the DMUs should be three times more than the number of input and output variables used (Golany and Roll, 1989; Masiye, 2007), hence, it was not a binding constraint (Hollingsworth and Peacock, 2008).

Sensitivity analyses were conducted using two different DEA estimation techniques and various combinations of input and output variables. The two estimation techniques employed here were implemented using two Stata commands: *teradial* and *simarwilson*. The *teradial* command fits DEA models where original radial technical efficiency measures are computed (Fare 1998; Fare and Lovell 1978; Fare, Grosskopf, and Lovell 1994a; Badunenko and Mozharovskyi, 2016) whilst the *simarwilson* command implements DEA two-stage bootstrap bias-corrected radial technical efficiency measures (Simar and Wilson, 1998; 2000; 2002; 2018). The comparison of the technical efficiency estimates from the two estimation techniques (see Appendix C) showed a highly significant positive Spearman rank correlation across all the three models: Model 1 $(\rho = 0.98, P < 0.01)$; Model 2 $(\rho = 0.84, P < 0.01)$; and Model 3 $(\rho = 0.59, P < 0.01)$. Again, consistent results were obtained from various combinations of input and output variables, which strengthens the validity of the findings from this study. For example, the sensitivity of the results obtained from Model 3 was tested, particularly because two of the inputs employed (i.e. inpatient beds per thousand population and physicians per thousand population) are less frequently reported on across SSA countries. When they were replaced by health expenditure per capita (constant at 2011 PPP), it was found that the results did not change significantly.

In order to assess the robustness of the results obtained from the bootstrap regression procedures in the second-stage analysis, the more usual truncated regression procedure was also applied (see Appendix D). The striking similarities of the estimated coefficients in terms of both numerical values and statistical significance across different models and estimation methods confer robustness to the empirical evidence, which enhances confidence in the arrived conclusions.

According to Greene (2004), there is no well-defined theory to guide the selection of environmental and policy variables in the second-stage regression analysis. The choice then becomes empirical. However, in order to discriminate between different competing specifications of the models, the log likelihood ratio test for nested models was used. The test statistics, as reported on Table 6, favor model specifications with interaction terms (A) as against parsimonious specifications (B), at least for Models 1 and 3, since the inclusion of the interaction terms improves the fitness of the models. Accordingly, we report results of model specifications involving the interaction terms for all the three models.

Table 6. Log likelihood ratio test results

Models	Competing Specifications	Value of test statistic	Conclusion
1	A versus B	5.72 (0.0573)	A is superior to B
2	A versus B	11.06 (0.0040)	A is superior to B

Notes. A = specification with interaction terms; B= parsimonious specification; probabilities values in parentheses.

4. Conclusion and Policy Implications

This study has examined the technical efficiency and its determinants of health systems of 44 SSA countries in curbing the COVID-19 pandemic using three different empirical DEA models. A review of the existing literature revealed an acute insufficient empirical research related to the efficiency of health systems in fighting an outbreak of diseases in general and COVID-19 in particular. Even though several studies have been undertaken to assess how countries in the sub-region can improve their health systems to contain outbreaks of diseases or pandemics, there is little or no known study that examines the efficiency of health systems in fighting pandemics. This paper contributes to fill this gap in the empirical literature. The overarching goal of this study was to assess the technical efficiency of health systems in SSA in curbing the COVID-19 pandemic and identifying the sources of inefficiencies. This general goal was divided into three specific objectives, using three different empirical frontier models to achieve the respective objectives.

The first empirical frontier model was to assess the technical efficiency of public health measures instituted by the various health systems in SSA to contain an outbreak of epidemic or pandemic in general and COVID-19 contagion in particular. The study evaluated the public health measures by assessing the outputs (inverse of COVID-19 cases per one million population) against the inputs directly used as public health measures (average of 13 IHRCC indicators and average of NPI stringency measures). The results from the first stage revealed that inefficiencies were quite high and that countries could have increased the results by 45% using the same resources. It was observed that the average efficiency scores decreased from low-income countries to lower-middle-income and upper-middle-income countries. This finding contradicts some international studies (Ahmed et al., 2019; Grosskopf, Self, and Zaim, 2006) which found that health systems performance was relatively more efficient in the developed countries. The second-stage analysis shows that GDP per capita and population density significantly worsen the health systems performance in terms of using public health measures to curb the spread of COVID-19 virus.

The second empirical model focused on measurement of the level of technical efficiency of the studied countries in flattening the COVID-19 contagion curve (i.e. reducing the rate of infections). This was done by evaluating the output (the number of days left in the cycle) against the inputs directly employed to flatten the curve (number of COVID-19 tests per one million population, NPIs stringency index, and healthcare expenditure as a percentage of GDP). The first-stage analysis revealed that health systems in SSA could have improved the results obtained by 36% given the same resources and the public health measures implemented. Again, the average efficiency scores decreased from low-income (0.70) and lower-middle-income (0.63) countries to upper-middle-income countries (0.46). The second-stage procedure shows that temperature levels and population density are significantly and negatively correlated with the performance of health systems in reducing the rate of COVID-19 infections.

The final empirical frontier model examined the efficiency of medical treatments of COVID-19 patients of the healthcare systems in the SSA. The examination was carried out using two outputs (number of recovered COVID-19 patients per thousand cases and survival rate of COVID-19 patients) against four inputs (number of COVID-19 tests per one million population, NPIs Stringency Index, number of inpatient beds per thousand population, and number of physicians per thousand population). In this model, it was observed that the average efficiency scores increases from the low-income and lower-middle-income countries to upper-middle-income countries. The second-stage analysis shows that good governance and aged population are significantly and positively correlated with the performance of health systems, whereas GDP per capita and prevalence of tobacco consumption worsen the performance from the perspective of medical treatment of COVID-19 patients.

The general finding of the study suggests that there is more room for health systems in SSA to improve their technical efficiency in fighting the COVID-19 pandemic. The findings also suggest that specific environmental factors significantly influence the level of health systems efficiency. These findings provide important policy implications for health systems to improve the technical efficiency in curbing the COVID-19 pandemic in particular, and by inference any other health epidemic or pandemic that may occur in future, by learning from the good performers (benchmarks).

One major revelation from this study is that countries that have made key investments in their health infrastructure and human resources are more efficient in managing the COVID-19 pandemic, at least in terms of the medical treatment of people who become infected with the virus. This implies the need for investment and political will to improve the public health institutions, medical facilities, and scientific expertise to prevent, control, and manage future outbreaks of epidemics. Second, the African Center for Disease Control and Prevention (i.e. Africa CDC) and its five regional collaborating centres must be supported by the Africa Union to carry out its mandate of strengthening and improving the capacity of public health institutions on the sub-region to detect and respond quickly and effectively to threats and outbreaks of diseases based on data- and science-driven interventions. Third, countries in the SSA must take this COVID-19 pandemic period as an opportunity to invest in research into local traditional medicines to reduce reliance on the West for orthodox medicine and vaccines.

Again, Ministries of health, which are mandated to supervise and regulate healthcare delivery, in the various countries must prioritize efficiency of healthcare facilities and personnel prior to and during outbreak of health pandemics. They can do this by strengthening their supervision, monitoring, and training divisions. At the facility level, timely design and distribution of protocols in caring for infected persons, right at the onset of the pandemic and human resource strategies geared towards recruiting and/or retaining well-qualified and experienced healthcare workers to provide professional services would prove critical in containing pandemics of this nature. This can be done by providing both intrinsic and extrinsic motivational packages, not only at the height of pandemics, but throughout their working lifespan.

This current study, like any other research work, suffers from some limitations which present an opportunity for refining and extending the frontiers of the outcomes of this study. The empirical analyses of this study are based on a snapshot of cross-sectional data spanning from 2016 to 2021 and the regression results are largely explorative, hence, places some restrictions on the current relevance and conclusions regarding the levels of health systems efficiency and the sources of inefficiency. It is, therefore, recommended that an extensive qualitative research be conducted in future to carry out in-depth analyses of best performing health systems in order to share best practices across the sub-region.

Another limitation of this study might emanate from the use of the DEA methodology. Since DEA is sensitive to the numeric values in the dataset and relies on the most efficient DMUs for frontier estimation, the use of different set of variables might give different results and conclusions (Hollingsworth and Peacock, 2008). Further, the use of relatively small number of DMUs might have led to overestimation of efficiency scores (Spinks and Hollingsworth, 2009). Future studies might increase the number of DMUs and explore additional variables, as data become available, in order to enhance the understanding of health system efficiency with a greater degree of complexity in curbing outbreak of epidemics and pandemics.

Findings from this study indicate that the most important determinants of health system efficiency in dealing with the COVID-19 pandemic are GDP per capita, population density, governance quality, tobacco use prevalence, and temperature levels. However, health systems have additional policy and environmental features that are not captured here, but might contribute to efficiency, such as financing mechanism, gatekeeping arrangements, burden of diseases, different political institutions, degree of centralization of decision-making within each system, hhealth-seeking behaviors, *inter alia*. Future studies might explore the use of these alternative health systems features in efficiency estimation and its determinants. Again, since untimely access to healthcare can either kill or reduce the quality of life of those who survive, future research could improve the outcome variables by measuring preventable years lost both to death and to poor quality of life.

Competing Interests Statement

The authors declare that there are no competing or potential conflicts of interest.

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APPENDIX A. WHO State Parties Self-Assessment Annual Reports (SPAR) Scores per Capacities and Average Total Score*

Country	AVE[a]	LAB[b]	RE[c]	FS[d]	ZOO[e]	LNF[f]	CE[g]	RC[h]	SUR[i]	HR[j]	NHE[k]	HSP[l]	POE[m]	IHRC[n]
Angola	63	80	60	40	80	20	40	80	100	60	73	53	30	100
Burundi	48	100	60	40	60	20	40	40	70	60	30	40	40	20
Benin	35	60	20	40	20	20	20	40	50	60	27	27	20	47
Burkina Faso	44	60	40	20	40	100	20	40	70	80	33	40	30	27
Botswana	32	80	40	40	20	40	20	20	40	20	20	47	20	10
CAR	17	40	20	0	20	0	20	0	50	20	20	20	20	0
Côte d’Ivoire	44	80	40	20	60	20	100	20	30	80	33	27	30	90
Cameroon	42	20	40	40	80	20	20	20	60	60	33	33	30	20
Congo, DR.	35	40	20	20	60	40	20	20	40	60	33	27	30	47
Congo, Rep.	33	20	20	40	20	20	20	40	50	60	20	20	20	30
Comoros	27	20	0	60	60	20	20	40	40	20	33	20	10	20
Cabo Verde	48	80	20	80	40	60	40	40	60	40	40	53	40	73
Djibouti	32	20	0	40	40	40	40	20	60	20	20	33	30	53
Eritrea	49	80	20	20	80	20	20	80	50	80	20	80	50	63
Ethiopia	63	80	40	40	40	100	40	80	70	20	27	33	80	83
Gabon	27	20	20	20	20	20	20	20	40	40	20	27	10	63
Ghana	49	60	60	40	60	40	40	80	80	20	33	40	40	73
Guinea	44	80	20	20	60	60	20	40	80	40	47	33	40	37
Gambia	38	20	20	20	20	40	20	60	70	20	40	27	40	0
Guinea-Bissau	25	20	20	20	40	40	20	40	30	20	27	27	20	90
Equatorial Guinea	22	20	20	20	20	20	20	20	40	20	20	27	20	20
Kenya	43	40	20	60	60	60	40	40	50	20	33	40	50	20
Liberia	46	60	20	20	60	40	20	60	80	40	47	33	60	100
Lesotho	29	80	0	20	40	40	0	20	40	20	20	40	30	83
Madagascar	29	40	20	40	20	20	20	20	60	20	27	20	30	27
Mali	48	60	20	80	80	60	20	60	70	40	55	33	20	30
Mozambique	60	80	40	60	80	40	40	80	80	80	67	53	40	83
Mauritania	35	60	40	20	80	40	20	20	40	20	47	40	20	40

Mauritius	64	100	40	80	20	100	40	80	70	80	67	73	80	100
Malawi	35	80	0	40	40	20	0	20	80	80	27	53	20	100
Namibia	59	100	40	60	80	60	40	40	80	60	33	73	60	90
Niger	39	80	20	20	20	20	40	20	80	80	27	27	20	83
Nigeria	51	40	60	40	60	40	20	20	70	60	47	33	50	83
Rwanda	71	100	40	100	80	100	40	100	70	60	47	67	40	73
Senegal	54	60	20	80	60	40	60	40	50	60	53	40	40	10
Sierra Leone	40	60	20	20	40	60	20	80	60	20	67	33	40	100
Sao Tome and Principe	32	20	20	40	20	40	20	20	40	40	40	47	40	47
Eswatini	40	80	20	40	20	60	40	20	70	20	27	33	80	100
Seychelles	53	100	20	80	80	60	20	60	80	20	27	60	40	100
Chad	30	40	20	20	40	20	20	20	70	40	27	27	20	57
Togo	39	80	20	40	60	20	0	60	70	20	40	27	40	83
Uganda	66	100	60	40	60	60	80	80	80	80	80	67	40	53
South Africa	70	100	100	100	60	80	80	60	40	60	73	33	60	100
Zambia	60	60	40	40	60	80	40	40	70	80	67	67	80	63
Zimbabwe	50	80	40	80	80	40	40	20	70	60	27	40	30	67

[*]These are 2019 SPAR Scores used to measure the resilience and preparedness of national health systems against health emergency risks. [a] AVE = Average Total Score for the 2019 13 capacities SPAR Scores. [b] LAB = Laboratory refers to States parties' capacity to establish mechanisms that assure the reliable and timely laboratory identification of infectious agents and other hazards likely to cause public health emergencies of national and international concern, including shipment of specimens to the appropriate laboratories if necessary; [c] RE = Radiation Emergency refers to States parties' capacity to detect and respond to radiological and nuclear emergencies that may constitute a public health event of national or international concern; [d] FS = Food Safety refers to States parties' capacity to detect and respond to food safety events that may constitute a public health emergency of national or national or international concern; [e] ZOO = Zoonotic Events and the Human-Animal Interface refers to States parties' capacity to detect and respond to zoonotic events of national or international concern; [f] LNF = Legislation and Financing refers to States Parties' capacity to have an adequate legal framework to support and enable implementation of all of their obligations and rights; [g] CE = Chemical Events refers to States parties' capacity to detect and respond to chemical events of national and international public health concern; [h] RC = Risk Communication refers to States parties' capacity to help stakeholders define risks, identify hazards, assess vulnerabilities and promote community resilience, and disseminate information to the public about health risks and events; [i] SUR = Surveillance refers to States parties' capacity of rapid detection of public health risks, as well as the prompt risk assessment, notification, and response to these risks; [j] HR: Human Resource refers to States parties' capacity to strengthen the skills and competencies of public health personnel; [k] NHE = National Health Emergency Framework refers to States parties' capacity to facilitate the coordination and management of outbreak operations and other public health events, and capacity to develop national, intermediate and community/primary response level public health emergency response plans for relevant biological, chemical, radiological and nuclear hazards; [l] HSP = Health Service Provision refers to States parties' capacity to provide high-quality health service; [m] POE = Point of Entry refers to States parties' capacity to establish effective surveillance and response at points of entry, and fulfill general obligation; n IHRC = IHR Coordination and National IHR Focal Point Function refers to States parties' capacity to coordinate nationwide resources, including the designation of an National IHR Focal Point. IHR: International Health Regulation; WHO: World Health Organization.

APPENDIX B: Codebook for Covid-19 Government Response Tracker

ID	Name	Description	Measurement	Coding
C1	C1_School closing	Record closings of schools and universities	Ordinal scale	0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, e.g. just high school, or just public schools) 3 - require closing all levels Blank - no data
	C1_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C2	C2_Workplace closing	Record closings of workplaces	Ordinal scale	0 - no measures 1 - recommend closing (or recommend work from home) 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (e.g. grocery stores, doctors) Blank - no data
	C2_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C3	C3_Cancel public events	Record cancelling public events	Ordinal scale	0 - no measures 1 - recommend cancelling 2 - require cancelling Blank - no data
	C3_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C4	C4_Restrictions on gatherings	Record limits on gatherings	Ordinal scale	0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less Blank - no data

	C4_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C5	C5_Close public transport	Record closing of public transport	Ordinal scale	0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it) Blank - no data
	C5_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C6	C6_Stay at home requirements	Record orders to "shelter-in-place" and otherwise confine to the home	Ordinal scale	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (e.g. allowed to leave once a week, or only one person can leave at a time, etc.) Blank - no data
	C6_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C7	C7_Restrictions on internal movement	Record restrictions on internal movement between cities/ regions	Ordinal scale	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place Blank - no data
	C7_Flag		Binary flag for geographic scope	0 - targeted 1- general Blank - no data
C8	C8_International travel controls	Record restrictions on international travel Note: this records policy for foreign travelers, not citizens	Ordinal scale	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure Blank - no data
H1	H1_Public information	Record presence of public info campaigns	Ordinal scale	0 - no Covid-19 public information campaign 1 - public officials urging caution about Covid-19

campaigns		2- coordinated public information campaign (eg across traditional and social media) Blank - no data
H1_Flag	Binary flag for geographic scope	0 - targeted 1- general Blank - no data

Source: Hale, Angrist, Cameron-Blake, et al., 2020

APPENDIX C. Farrell VRA Output-Oriented DEA, Bias, and Bias-Corrected Technical Efficiency Scores

Country	COVID-19 Public Health Efficiency Scores			Flattening COVID-19 Curve Efficiency Scores			COVID-19 Medical Treatment Efficiency Scores		
	DEA	Bias	BC DEA	DEA	Bias	BC DEA	DEA	Bias	BC DEA
Angola	1.264	-0.195	1.458	1.000	-0.175	1.182	1.014	-0.009	1.022
Burundi	1.000	-0.376	1.380	1.000	-0.563	1.559	1.000	-0.010	1.009
Benin	1.363	-0.302	1.664	1.000	-0.787	1.789	1.008	-0.003	1.011
Burkina Faso	1.364	-0.218	1.581	1.270	-0.149	1.417	1.000	-0.017	1.018
Botswana	1.471	-0.427	1.899	2.128	-0.117	2.248	1.007	-0.002	1.009
Central African Rep.	1.000	-0.150	1.147	1.000	-0.092	1.091	1.000	-0.004	1.004
Cote d'Ivoire	1.613	-0.372	1.981	1.000	-0.170	1.169	1.000	-0.019	1.019
Cameroon	1.538	-0.250	1.787	1.000	-0.335	1.340	1.005	-0.006	1.011
Congo, Dem. Rep.	1.000	-0.229	1.234	1.000	-0.293	1.309	1.000	-0.018	1.018
Congo, Rep.	1.640	-0.422	2.060	1.000	-0.205	1.216	1.011	-0.003	1.014
Cabo Verde	1.679	-0.412	2.093	1.197	-0.059	1.257	1.003	-0.003	1.006
Ethiopia	1.704	-0.338	2.044	1.075	-0.082	1.157	1.000	-0.004	1.004
Gabon	1.700	-0.487	2.189	46.434	-10.41	57.084	1.001	-0.001	1.002
Ghana	1.680	-0.381	2.059	2.673	-0.406	3.076	1.001	-0.003	1.004
Guinea	1.568	-0.287	1.853	1.065	-0.053	1.118	1.000	-0.005	1.005
Gambia, The	1.614	-0.380	1.994	1.052	-0.133	1.191	1.028	-0.003	1.031
Guinea-Bissau	1.281	-0.301	1.583	1.000	-0.042	1.043	1.006	-0.004	1.010

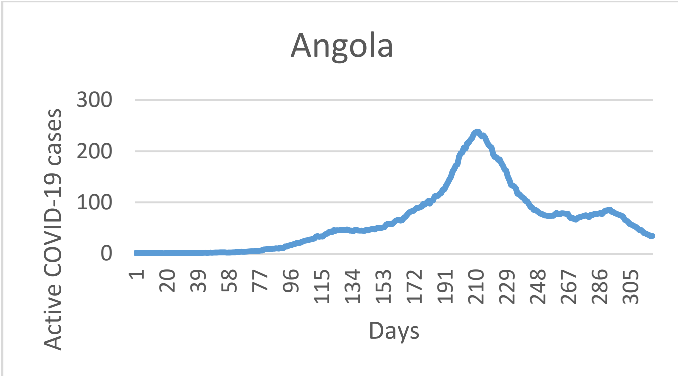
Equatorial Guinea	1.339	-0.298	1.635	1.064	-0.150	1.219	1.010	-0.004	1.014
Kenya	1.763	-0.413	2.176	1.232	-0.044	1.278	1.014	-0.003	1.017
Liberia	1.419	-0.268	1.686	1.023	-0.033	1.057	1.000	-0.004	1.004
Lesotho	1.000	-0.326	1.327	1.728	-0.056	1.785	1.024	-0.005	1.029
Madagascar	1.090	-0.200	1.293	1.000	-0.098	1.101	1.000	-0.063	1.062
Mali	1.208	-0.169	1.375	1.350	-0.181	1.528	1.030	-0.006	1.036
Mozambique	1.448	-0.249	1.698	2.053	-0.072	2.125	1.005	-0.004	1.010
Mauritania	1.620	-0.437	2.054	1.388	-0.131	1.521	1.007	-0.011	1.018
Mauritius	1.379	-0.364	1.743	1.000	-0.380	1.380	1.000	-0.002	1.002
Malawi	1.187	-0.256	1.441	1.910	-0.099	2.009	1.000	-0.004	1.004
Namibia	1.689	-0.373	2.060	1.530	-0.095	1.627	1.005	-0.003	1.008
Niger	1.000	-0.189	1.184	1.000	-0.310	1.297	1.000	-0.004	1.004
Nigeria	1.774	-0.252	2.024	1.708	-0.186	1.895	1.005	-0.007	1.012
Rwanda	1.708	-0.342	2.050	1.933	-0.063	2.000	1.006	-0.003	1.009
Senegal	1.964	-0.444	2.407	8.039	-0.711	8.755	1.000	-0.004	1.004
Sierra Leone	1.265	-0.303	1.565	1.919	-0.178	2.092	1.000	-0.014	1.014
Sao Tome & Principe	1.343	-0.379	1.723	1.025	-0.049	1.076	1.013	-0.002	1.015
Eswatini	1.813	-0.472	2.287	1.682	-0.062	1.747	1.036	-0.002	1.038
Seychelles	1.618	-0.360	1.975	47.128	-5.840	53.046	1.000	-0.002	1.002
Chad	1.000	-0.157	1.156	1.586	-0.141	1.729	1.014	-0.006	1.020
Togo	1.787	-0.390	2.176	3.493	-0.158	3.654	1.006	-0.003	1.009
Uganda	1.512	-0.295	1.806	1.380	-0.043	1.424	1.005	-0.003	1.008
South Africa	2.061	-0.483	2.543	1.640	-0.065	1.708	1.027	-0.003	1.030
Zambia	1.573	-0.343	1.912	1.822	-0.147	1.974	1.007	-0.003	1.010
Zimbabwe	1.615	-0.364	1.980	1.665	-0.051	1.717	1.037	-0.003	1.040

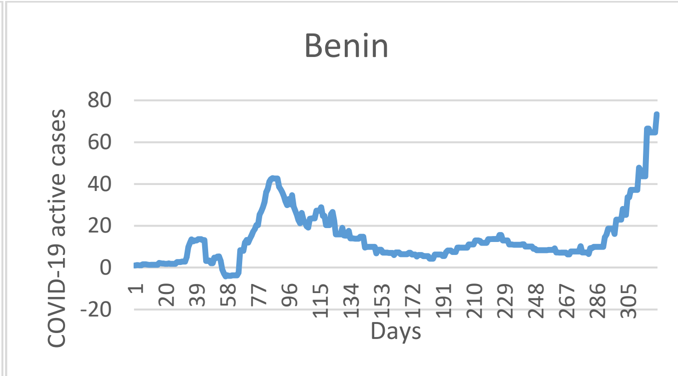
APPENDIX D: Truncated Regression Results (44 countries)

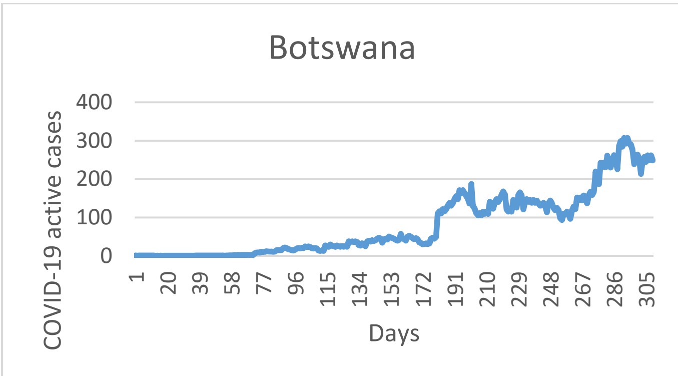
VARIABLES	MODEL 1	MODEL 2	MODEL 3
GDP	0.256*	0.0765	0.0139***
	(0.131)	(4.226)	(0.00371)
TOBACCO	-0.00622	-0.153	0.00165***
	(0.00711)	(0.245)	(0.000209)
AGED	0.0277	0.451	-0.00325**
	(0.0481)	(1.521)	(0.00141)
GOVERNANCE			-0.0106***
			(0.00285)
TEMPERATURE		0.626	
		(0.479)	
DENSITY	0.145***	1.044	-0.00144
	(0.0501)	(1.687)	(0.00147)
2.LOWER-MIDDLE-INCOME	0.726*	6.433	-0.0380***
	(0.407)	(13.03)	(0.0112)
3.UPPER-MIDDLE-INCOME	0.687	17.04	-0.0385***
	(0.430)	(14.73)	(0.0121)
2.INCGROUP#c.DENSITY	-0.160*	-1.411	0.00714***
	(0.0875)	(2.773)	(0.00241)
7.INCGROUP#c.DENSITY	-0.242***	-0.616	0.00122
	(0.0909)	(3.000)	(0.00274)
CONSTANT	-0.878	-19.11	0.899***
	(0.974)	(32.23)	(0.0302)
SIGMA	0.249***	7.871***	0.00682***
	(0.0265)	(0.839)	(0.000727)

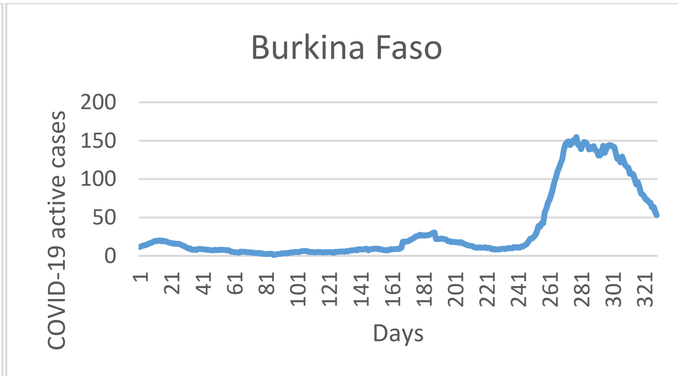
Notes. Standard errors in parentheses. Dependent variables: inefficiency scores ($i.e. \theta_m^* > 1$). *** p<0.01, ** p<0.05, * p<0.1

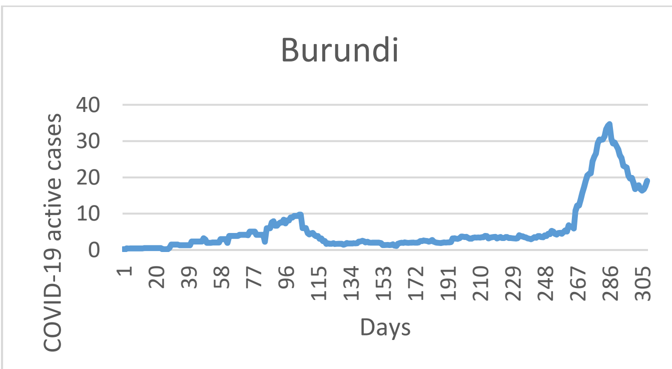
APPENDIX E: Epidemiological Curves for COVID-19 Active Cases

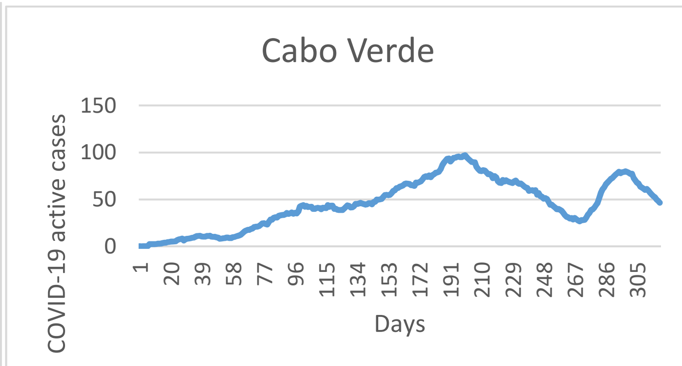


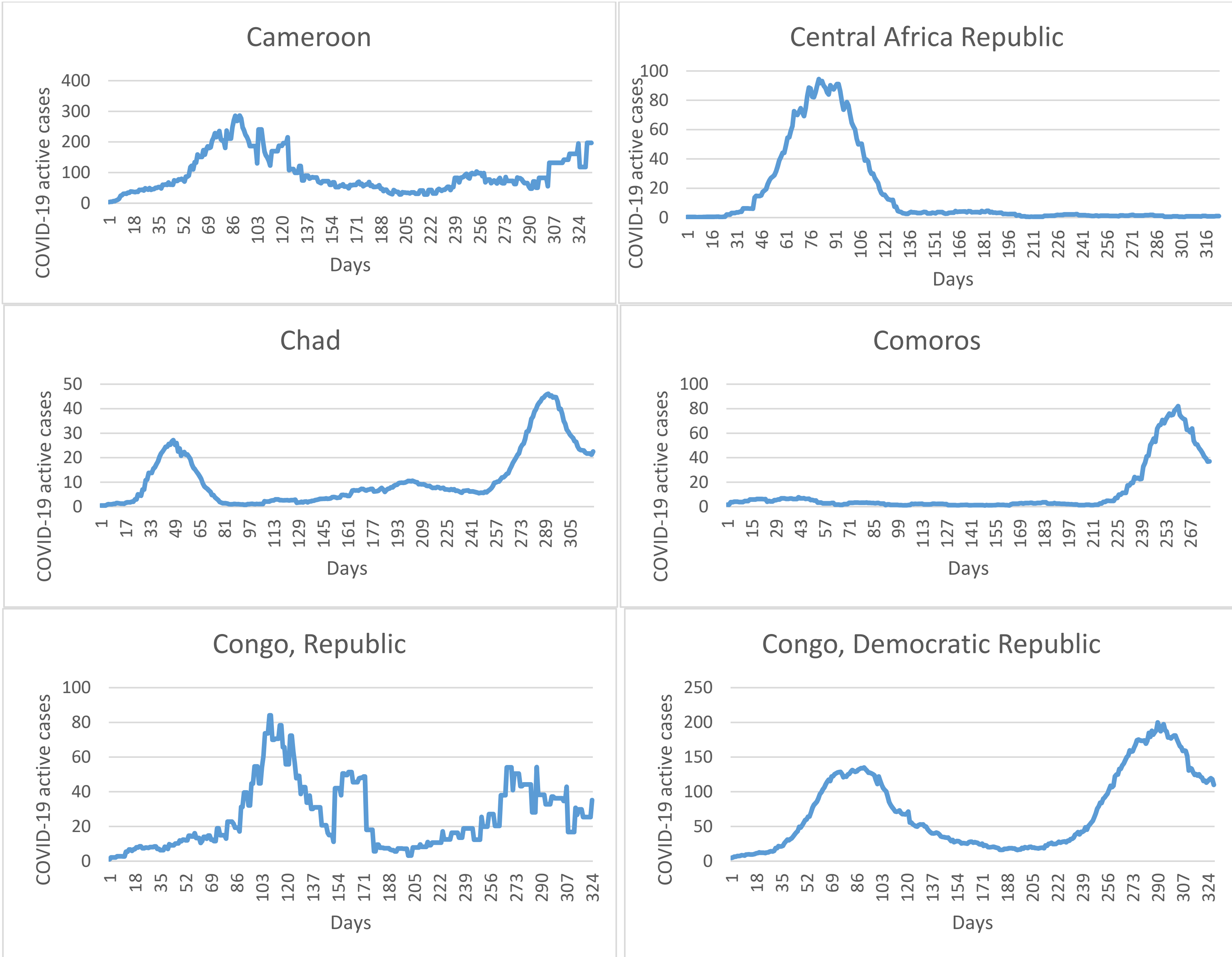


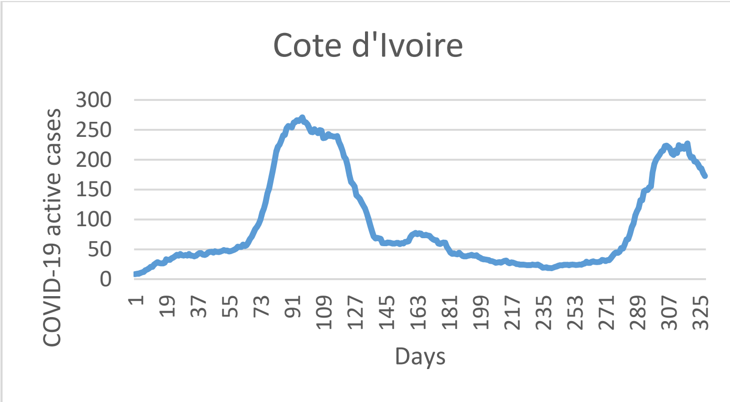


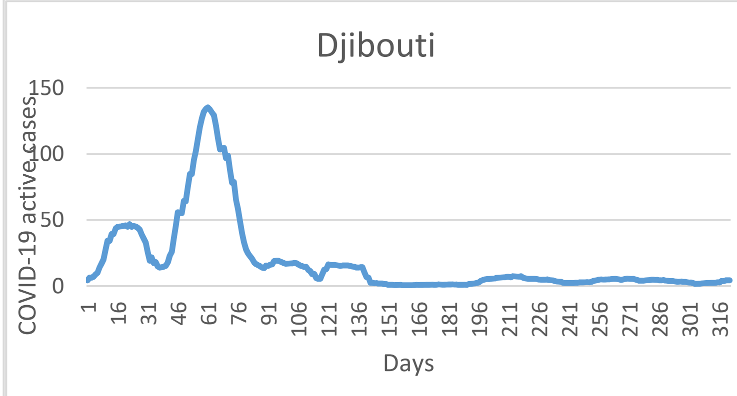


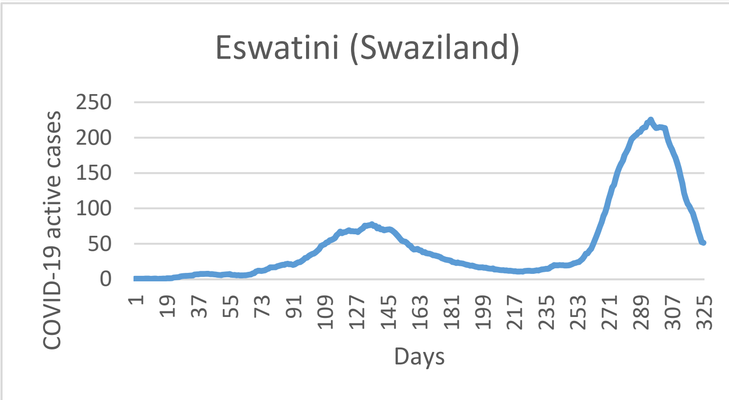


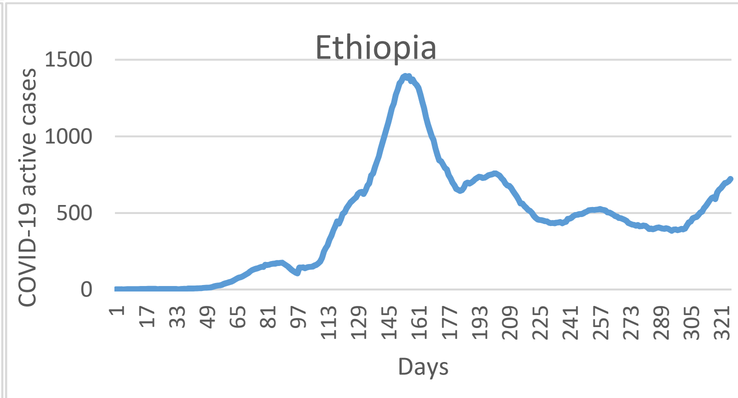



Cameroon
COVID-19 active cases
400
300
200
100
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307 324
Days
Central Africa Republic
COVID-19 active cases
100
80
60
40
20
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301 316
Days
Chad
COVID-19 active cases
50
40
30
20
10
0
1 17 33 49 65 81 97 113 129 145 161 177 193 209 225 241 257 273 289 305
Days
Comoros
COVID-19 active cases
100
80
60
40
20
0
1 15 29 43 57 71 85 99 113 127 141 155 169 183 197 211 225 239 253 267
Days
Congo, Republic
COVID-19 active cases
100
80
60
40
20
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307 324
Days
Congo, Democratic Republic
COVID-19 active cases
250
200
150
100
50
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307 324
Days


Cote d'Ivoire
COVID-19 active cases
300
250
200
150
100
50
0
1 19 37 55 73 91 109 127 145 163 181 199 217 235 253 271 289 307 325
Days


Djibouti
COVID-19 active cases
150
100
50
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301 316
Days


Eswatini (Swaziland)
COVID-19 active cases
250
200
150
100
50
0
1 19 37 55 73 91 109 127 145 163 181 199 217 235 253 271 289 307 325
Days


Ethiopia
COVID-19 active cases
1500
1000
500
0
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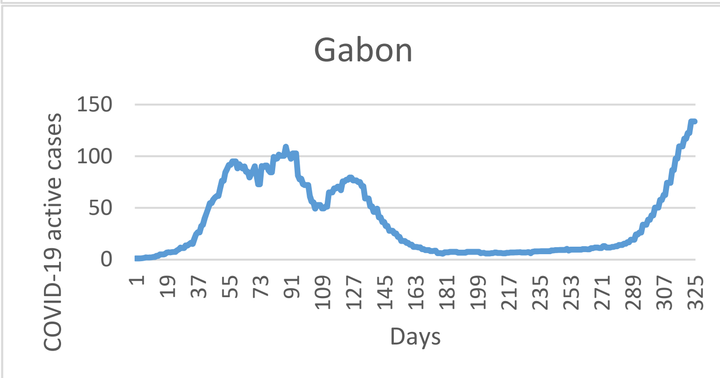
Days


Gabon
COVID-19 active cases
150
100
50
0
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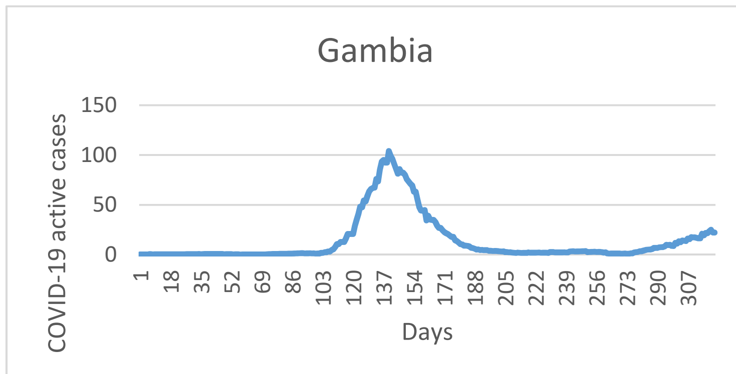
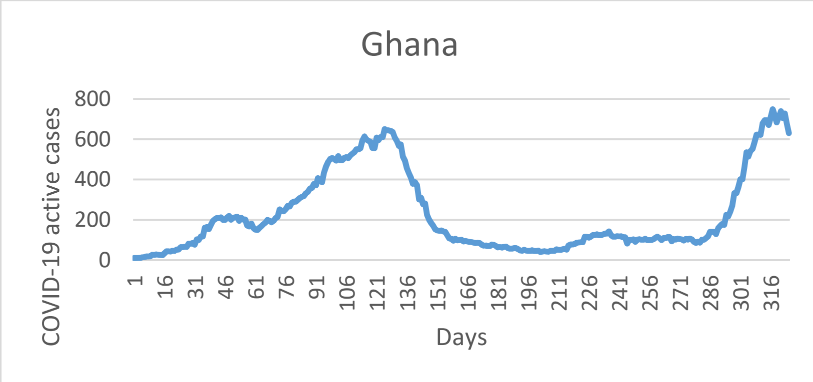
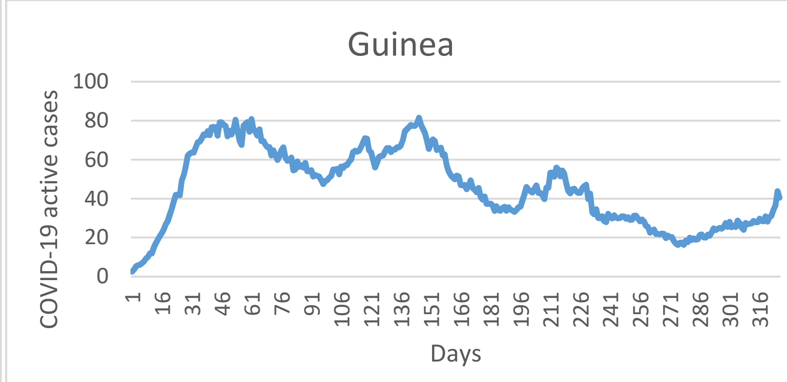
Days


Gambia
COVID-19 active cases
150
100
50
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307
Days


Ghana
COVID-19 active cases
800
600
400
200
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301 316
Days


Guinea
COVID-19 active cases
100
80
60
40
20
0
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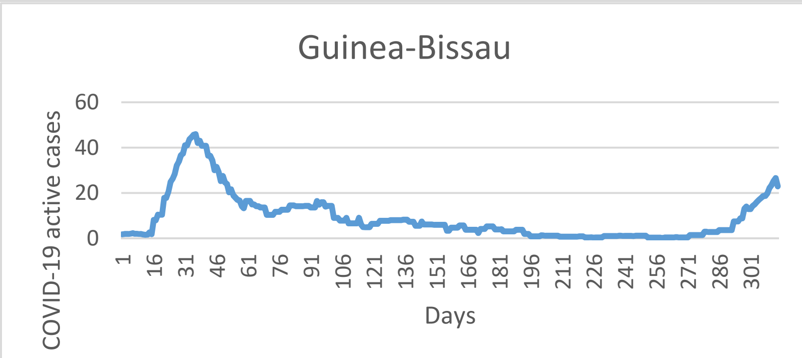
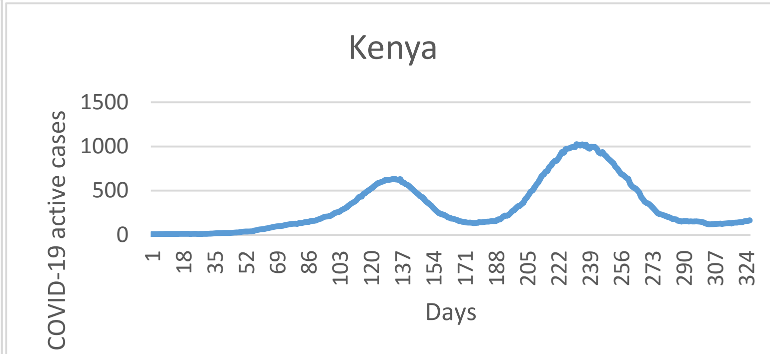
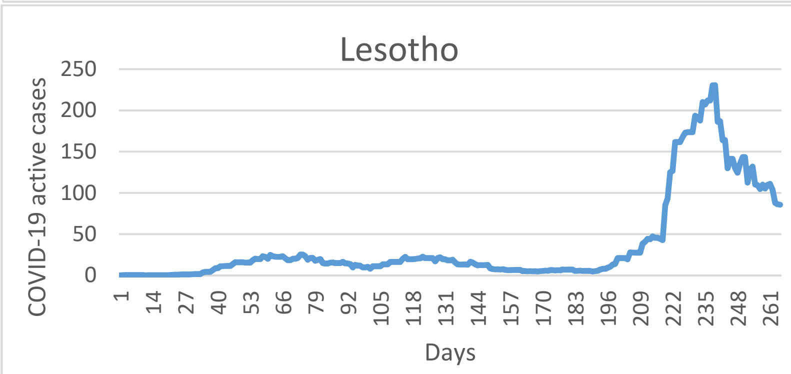
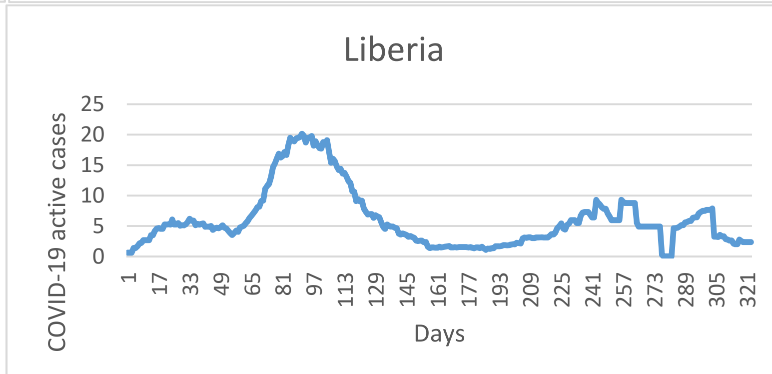
Days


Guinea-Bissau
COVID-19 active cases
60
40
20
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301
Days


Kenya
COVID-19 active cases
1500
1000
500
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307 324
Days


Lesotho
COVID-19 active cases
250
200
150
100
50
0
1 14 27 40 53 66 79 92 105 118 131 144 157 170 183 196 209 222 235 248 261
Days


Liberia
COVID-19 active cases
25
20
15
10
5
0
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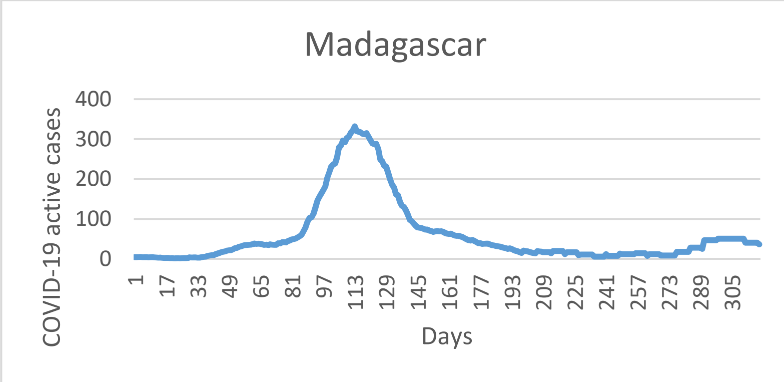
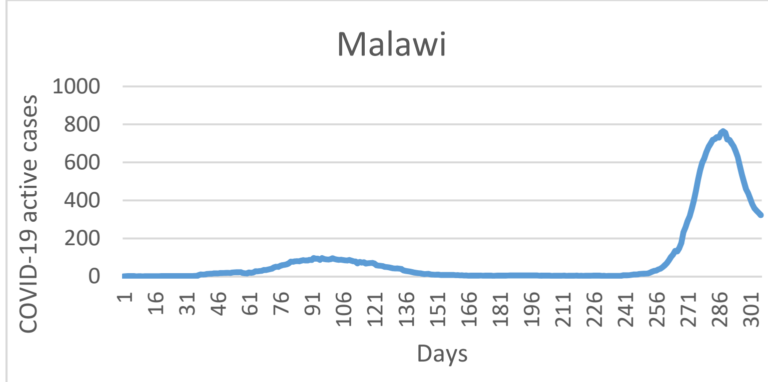
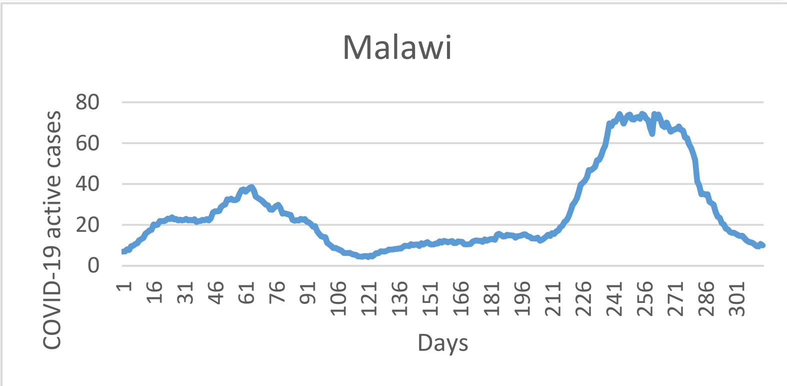
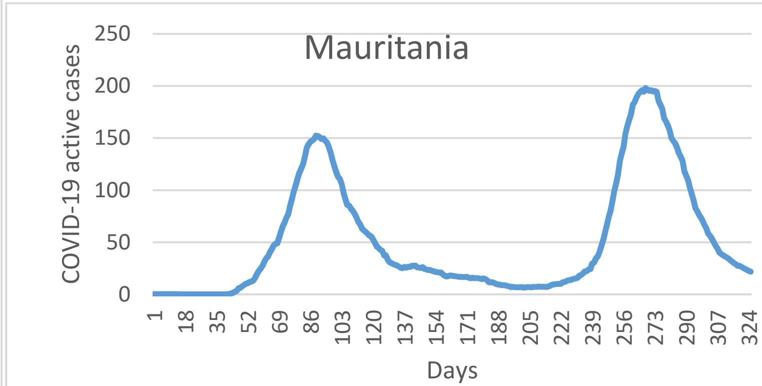
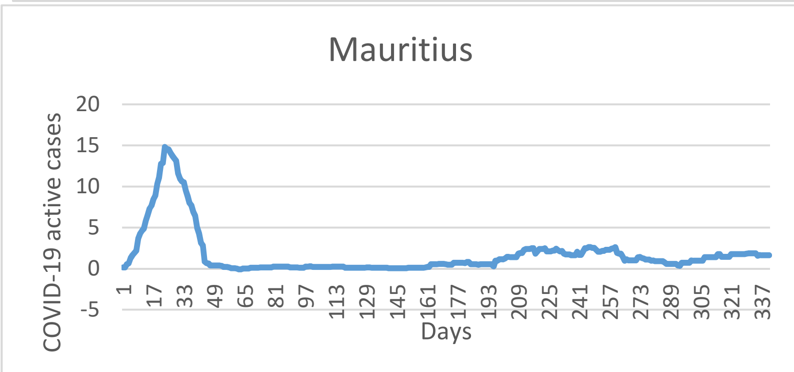
Days


Madagascar
COVID-19 active cases
400
300
200
100
0
1 17 33 49 65 81 97 113 129 145 161 177 193 209 225 241 257 273 289 305
Days


Malawi
COVID-19 active cases
1000
800
600
400
200
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301
Days


Malawi
COVID-19 active cases
80
60
40
20
0
1 16 31 46 61 76 91 106 121 136 151 166 181 196 211 226 241 256 271 286 301
Days


Mauritania
COVID-19 active cases
250
200
150
100
50
0
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 256 273 290 307 324
Days


Mauritius
COVID-19 active cases
20
15
10
5
0
-5
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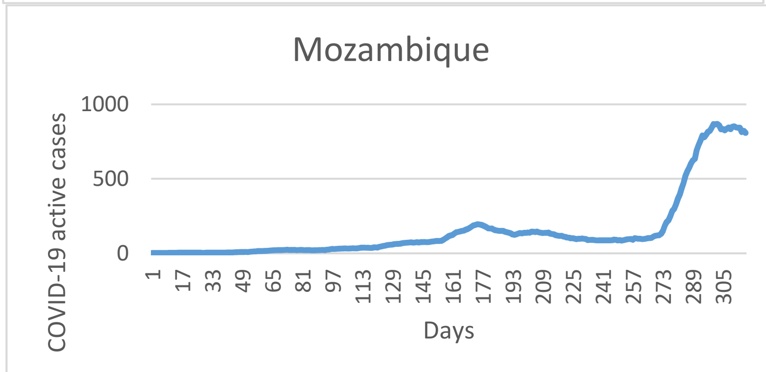
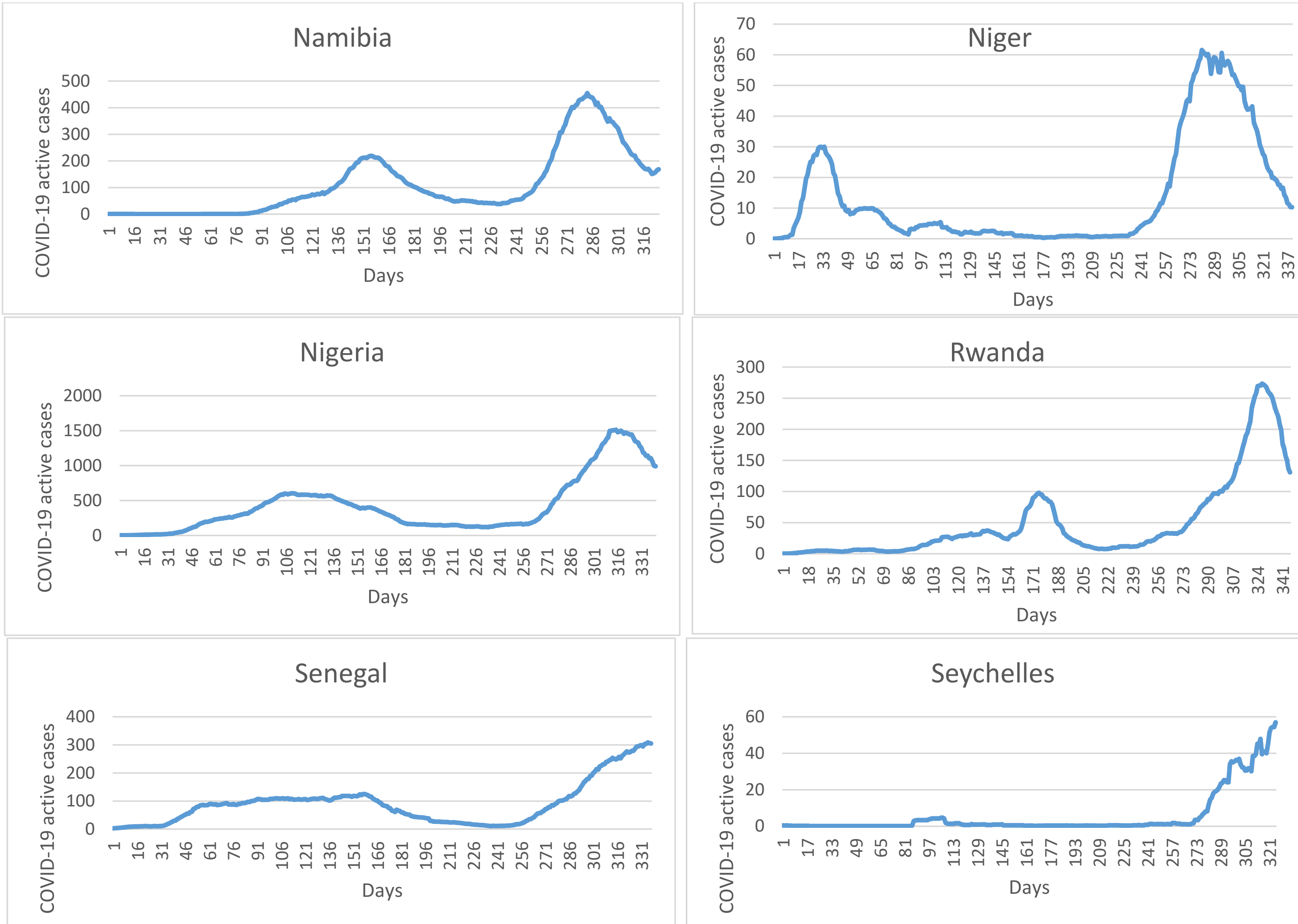
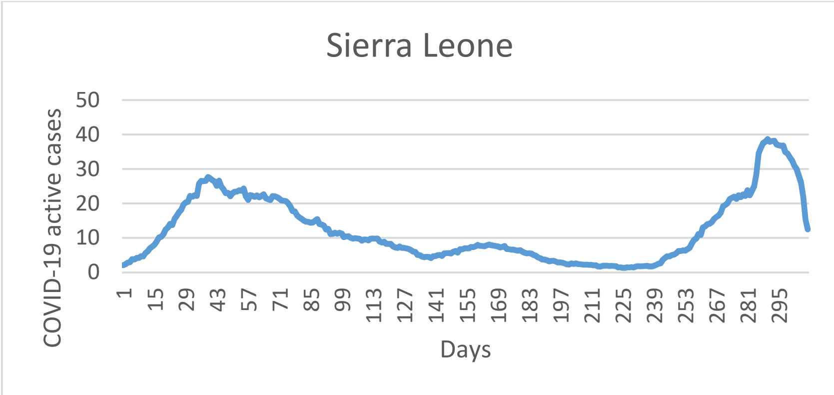
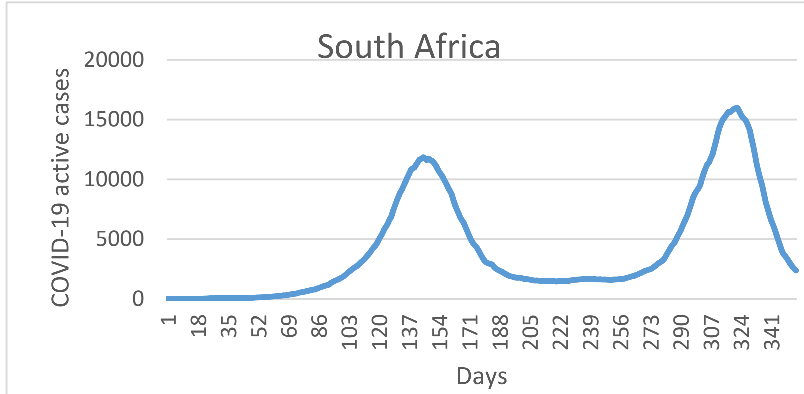
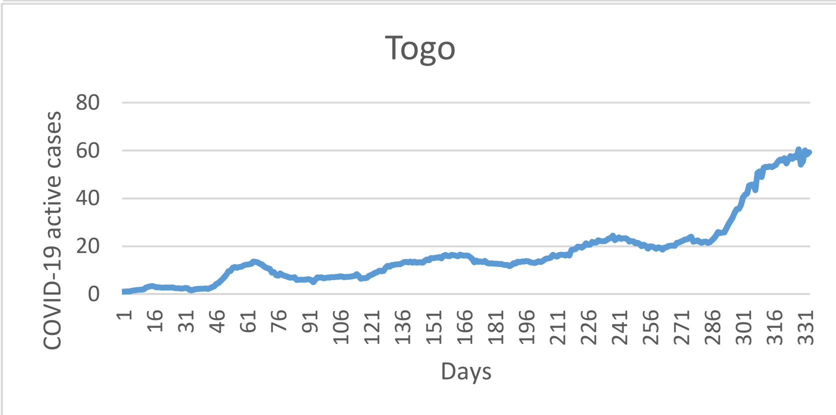
Days

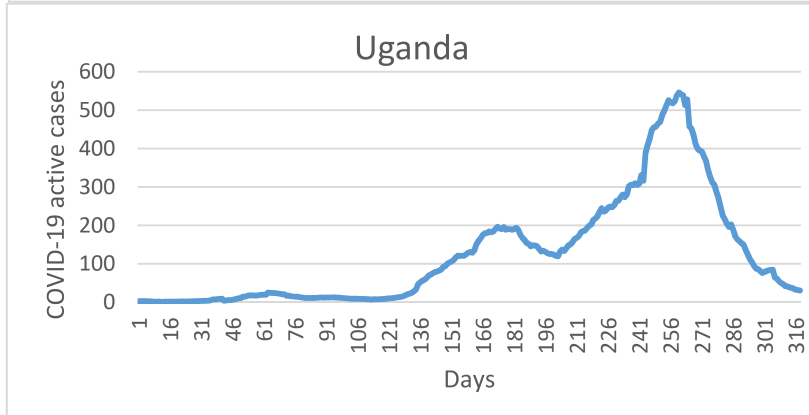

Mozambique
COVID-19 active cases
1000
500
0
1 17 33 49 65 81 97 113 129 145 161 177 193 209 225 241 257 273 289 305
Days

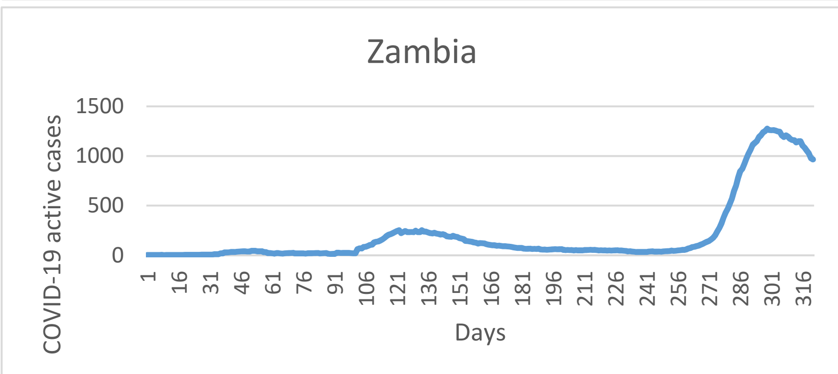

Namibia
COVID-19 active cases
Days
Niger
COVID-19 active cases
Days
Nigeria
COVID-19 active cases
Days
Rwanda
COVID-19 active cases
Days
Senegal
COVID-19 active cases
Days
Seychelles
COVID-19 active cases
Days

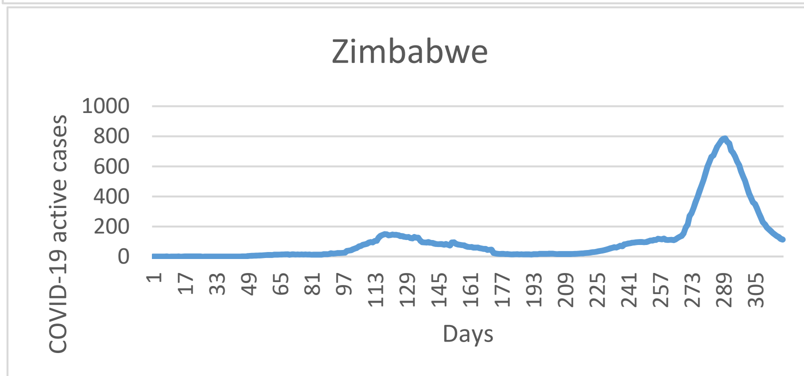

Sierra Leone
COVID-19 active cases
Days


South Africa
COVID-19 active cases
Days


Togo
COVID-19 active cases
Days


Uganda
COVID-19 active cases
Days


Zambia
COVID-19 active cases
Days


Zimbabwe
COVID-19 active cases
Days