Social Indicators Research (2019) 143:371–389
https://doi.org/10.1007/s11205-018-1969-1

An Estimation of the Efficiency and Productivity of Healthcare Systems in Sub-Saharan Africa: Health-Centred Millennium Development Goal-Based Evidence

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Accepted: 11 July 2018 / Published online: 14 July 2018

Abstract

The millennium development goals (MDGs) were designed to realign national priorities towards human development of which healthcare is the foundation. An extension of the MDGs, the sustainable development goals (SDGs), has more recently been introduced and has become the core focus for Sub-Saharan Africa (SSA) regardless of her performance vis-à-vis the MDGs. A transition into accomplishing the SDGs without identifying the efficiency and determinants of the shortfall in achieving the MDGs is a flawed approach. This paper seeks to estimate the efficiency of healthcare systems in SSA based on health focused MDGs. We estimate the technical efficiency and total factor productivity of these systems, and rank the annual performance of SSA's healthcare systems from 2010 to 2015 using a robust data envelopment analysis (DEA) approach. Regression analysis is applied to the determinants of healthcare system efficiency. The DEA results show healthcare systems in SSA to be inefficient, with only three countries; Botswana in 2015, Rwanda in 2014 and 2015, and Tanzania in 2015; identified as efficient over the evaluated period. Failure to achieve technological advancements is the identified leading cause of a decrease in productivity. Scale inefficiency is determined to be the primary cause of technical inefficiency. The study also shows that governance measures, i.e., the rule of law and government efficacy, impact healthcare system efficiency more than public expenditure on health, indicating that the volume of resources invested in healthcare systems is not as important as the efficient management of the said resources in SSA countries.

Keywords Healthcare system · Efficiency · Total factor productivity · Sub-Saharan Africa · Order-alpha · Data envelopment analysis

Supplementary data associated with this article can be found at: https://data.mendeley.com/datasets/4ppyt2bnx5/draft?a=28eeb9dc-7e31-431e-8375-58f5513b26a7.

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1 Introduction

The millennium development goals (MDGs) indicate that health is a crucial component in socio-economic progress (Ong et al. 2009). Three of the eight MDGs focus primarily on improving health production,—reducing child mortality, improving maternal health, and combating HIV/AIDS, malaria and other diseases (Azevedo 2017; Alhassan et al. 2015; Asandului et al. 2014). According to a United Nations report (UN 2008), most African countries have made little progress in achieving the MDGs.

The Governments of African countries and international development partners are committed to meeting the newly introduced sustainable development goals (SDGs) which build on the MDGs concluded in 2015, so as to ensure the health and well-being of all population (goal 3). However, the pre-MDGs' problems, specifically health-related MDGs, still persist in Sub-Saharan Africa (SSA). A UN report in 2015 on MDG assessment shows that SSA did not meet most MDGs by the 2015 target, with another report stating that most African countries will meet the MDGs target 25 years after the 2015 target (Afikanza 2014). It is a fair conclusion that the SDGs are built on a weak foundation, thus making such commitments futile, especially without empirical evidence to understand the reasons for the shortfall in achieving the MDGs. Both MDGs and SDGs were designed to influence realignment of national priorities towards human development of which healthcare is the foundation. A transition into accomplishing the SDGs without identifying the relative performance and determinants of the shortfall in achieving the MDGs in SSA is a flawed approach. It is our opinion that for the target of the health MDGs to be achieved 25 years after 2015, or for the SDGs to come to fruition, the relative efficiency and drivers of the MDGs, which is the foundation of the SDGs, should be evaluated, and sufficient attention has to be directed towards the health MDGs. Hence, the motivation for this study.

Achieving the MDGs requires an efficient healthcare system to help fast-track the process. Optimal impact can be achieved by reducing inefficiency, which in turn will lead to a substantial improvement in the healthcare system. Inefficient systems should be moderated and adapted to expedite the establishment of efficient system practices. In order to enhance performance, it is imperative to quantify efficiency and determine efficiency drivers. This approach has been used since the early 2000s (Murray and Frenk 2000; Hollingsworth 2003).

The world health organization (WHO) ranks country performance according to health outcomes, responsiveness and health financing. Data envelopment analysis (DEA) is a tool in health systems research (Grausová et al. 2014; Hadad et al. 2013; Luasa et al. 2016; Medeiros and Schwierz 2015; Mills 2014; Ortega et al. 2017; Popescu et al. 2014; Akazili et al. 2008; Ozcan and Khushalani 2017), and is used to formulate strategies and policies to improve underperforming healthcare systems via the quantification of the national healthcare system and the identification of drivers of efficiency (Ozcan 2008). Quantification of healthcare systems implies measuring maternal, newborn, reproductive and child health commodities prioritized by the UN commission on life saving (USAID 2016). Healthcare system efficiency are analysed using either a parametric approach (e.g. stochastic frontier analysis) or a non-parametric approach (e.g. the DEA method) (Boerma et al. 2009). Generally, any variation in the efficiency of a healthcare system in achieving health goals is influenced by socio-economic status e.g. gross domestic product (GDP) per capita and income inequality (Greene 2004).

SSA is known to have relatively weak healthcare systems, whose efficiency is rarely investigated. However, (Bryan et al. 2010) stated that system wide barriers are impeding greater progress in SSA healthcare system, and proposed a diagnostic approach that is adaptable to any SSA healthcare system. (Kirigia 2015) analyzed the efficiency of health units in Africa. He attributed the cause of the relatively weak healthcare system to health leadership and governance, health workforce, service delivery, vaccines, health information and technology, and health financing. (Azevedo 2017) examined Africa's performance on the MDGs, and mentioned that Rwanda, Eritrea and Botswana are among the SSA countries that have made strides in the health MDGs. Given the rarity of studies on healthcare system efficiency in Africa, the current study is designed according to the methodology applied in preceding studies on healthcare systems (Retzlaff-Roberts et al. 2004; Sun et al. 2017; Valdmanis et al. 2017; Grausová et al. 2014; Hadad et al. 2013), with the aim of answering the following questions: how efficient is SSA's healthcare systems? How have they progressed? What are the causes of efficiency change? What are the drivers of healthcare system efficiency? And how can the efficiency be improved? In this context, health-related MDG indicators and health financing are included for the purpose of analysing and quantifying healthcare system efficiency. DEA is used to gauge efficiency and to rank SSA countries accordingly between 2010 and 2015. DEA is also used to examine changes in efficiency with respect to productivity in specified period. In addition, regression models are produced to examine drivers of health system efficiency and provide insight into factors associated with an improvement in healthcare system performance.

The paper is organised as follows: Sect. 2 reviews the materials and methods, and explains the data. Section 3 presents the results. Section 4 contains the discussion of the results and conclusion of the study, with suggestions for future study.

2 Materials and Methods

2.1 Materials and Data

The classical two-step framework of economic efficiency analysis that is usually employed in most studies is also applied to this one (Sun et al. 2017; Valdmanis et al. 2017; Hadad et al. 2013; Samut and Cafrı 2016). The efficiency and productivity of healthcare systems is initially evaluated using DEA. Thereafter, regression models are applied to identify the impact of the identified determinants on efficiency levels. Readily available public data from World Bank world development indicators are used in the efficiency and regression analysis. Four input and six output variables are selected for each country studied in this paper. We use these variables as indicators used to measure progress in meeting the goals and targets outlined in the MDGs (UN 2000).

Commonly used contextual factors that affect healthcare system efficiency directly (i.e., the inputs and outputs of a given healthcare system) are included. Since the objective is to assess the efficiency of healthcare systems, the variables chosen as inputs in the DEA model need to relate to the health production process as well as have an impact on population health. Health spending is an obvious choice as an input having been selected extensively in previous studies (Gearhart 2016; Hadad et al. 2013). Health expenditure per capita is used as an input in the DEA model. In order to standardize health expenditure across the different countries, data that had already been adjusted to a constant 2011 international currency ($), and which reflected purchasing power parity (PPP), is used. The literature demonstrates that (measles, diphtheria and pertussis [DTP] and hepatitis B third dose [HepB3]) prevents diseases and thus, impacts positively on population health (Popescu et al. 2014; Asandului et al. 2014). However, with the DEA model, efficiency is evaluated with the use of minimal inputs. Therefore, the immunisation rate is inverted to minimize the percentage of the non-immunized population in the efficiency evaluation in order to satisfy the DEA methodology (Asandului et al. 2014; Popescu et al. 2014). Indicators such as the number of health professionals (doctors or/and nurses), number of hospital beds and educational type (i.e., school) could not be used owing to the unavailability or lack of completeness of the data.

Products of the healthcare system i.e., life expectancy at birth, the infant mortality rate (IMR), MMR, number of tuberculosis cases, and newly infected HIV and malaria cases are selected as outputs in the current study. Life expectancy as an outcome has been used as an indicator of healthcare system performance in previous studies (Gearhart 2016; Hadad et al. 2013; Medeiros and Schwierz 2015). According to the DEA methodology, it is assumed that the larger the output, the greater the unit production. Thus, the IMR and MMR values are converted to infant survival rate (ISR) and maternal survival ratio (MSR) values (Afonso and St Aubyn 2005; Gearhart 2016; Adam et al. 2011; Samut and Cafrı 2016; Carrillo and Jorge 2017). Similarly, the inverse values of the number of tuberculosis cases, and newly infected HIV and malaria cases reported are used as outputs to satisfy the DEA model since they are also negative outputs.

Drivers of health system performance and determinants of national health system efficiency include economic factors, demographic factors, health financing and governance (Sun et al. 2017). Therefore, variables included in the regression model are GDP per capita (economic measure) urbanisation (demographic measure), public health expenditure as percentage of total health expenditure (measure of health financing), and government effectiveness and rule of law (measures of governance). Definition of variables used for the regression are presented in Table 1. Data on all five regressors are sourced from the World Bank world development indicators.

2.2 Data Envelopment Analysis (DEA)

Technical efficiency can be defined as the maximum amount of output that can be generated from a unit input, or the production of a unit output by investing minimum amount of inputs (Farrell 1957). It is inferred that in order to improve efficiency, it is necessary to increase the output per unit inputs invested or to decrease the input per unit outputs produced. The contribution of various resources to the health outcome of a population can be determined through an evaluation of healthcare system efficiency. DEA is a non-parametric frontier efficiency estimation method developed by (Charnes et al. 1978) to measure technical efficiency under constant returns to scale (CRS). It was later extended by (Banker et al. 1984) to address production efficiency under variable returns to scale (VRS). Subsequently, numerous models have been developed to advance the methodology. The VRS assumption may be appropriate in the context of the current study since it is adequate to assume that health is an increasingly concave function of health expenditure (Culyer and Wagstaff 1993; Hollingsworth and Wildman 2003).

Non-parametric estimators are preferred by researchers for the following reasons: they are not based on distributional assumption, and they are not restricted by specific production functions or error distribution. These factors make the incorporation of multiple inputs and outputs easy in efficiency evaluations. However, certain non-parametric estimators such as DEA suffer from the problem of having less than root-n convergence as a result of dimensionality and sensitivity to outliers, which underestimate some

Table 1 Variables employed in the regression

Variables	Definition
GDP per capita	GDP per capita, show economic growth, and reflects productivity of a country. It is the gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data are in constant 2010 US dollars
Urbanisation	Percentage of people living in urban areas as defined by national statistical offices
Rule of law (ROL)	ROF captures perceptions of the extent to which agents have confidence in and abide by the rules of society as well as the likelihood of crime and violence. Estimate gives the country's score in normalized values from −2.5 to 2.5 which are converted to percentile rank terms from 0 to 100, with higher values corresponding to better outcomes
Government effectiveness (GEFF)	GEFF captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Estimate gives the country's score in normalized values from −2.5 to 2.5 which are converted to percentile rank terms from 0 to 100, with higher values corresponding to better outcomes
Public health expenditure (% of total health expenditure)	Level of public health expenditure expressed as % of Total health expenditure (sum of public and private health expenditure) covering the provision of health services (preventive and curative), family planning activities, nutrition activities, and emergency aid designated for health but does not include provision of water and sanitation

efficiencies should they exist within the sample (Gearhart 2016; Kneip et al. 1998). The solution to the identified problems is to use a partial frontier lying "close to" the true production frontier which alleviates many of these problems. Two methods are available: (*order—m*) (Cazals et al. 2002) and (*order—α*) (Simar and Wilson 2008). The *order—α* estimator addresses the problem of dimensionality in the DEA estimator and, by design, achieves the classical parametric root-n convergence even though it is fully non-parametric (Kneip et al. 1998). The *order—m* is not used in this paper because the ability to empirically apply these estimators is still limited.

Efficiency evaluation using DEA has two main orientations: an input-oriented model and an output-oriented model. Efficiency is evaluated in an input-oriented model by ensuring that the outputs (health gains) remain constant while the inputs are decreased. Conversely, efficiency is assessed in an output-oriented model by ensuring that the inputs (health resources) remain constant while the outputs increase. The debate about which orientation is most suitable for an evaluation of healthcare system efficiency has been documented in literature. Often, the choice between input-orientation and output-orientation is arbitrary (Wheelock and Wilson 2009). In the current study, a newer non-parametric hyperbolic distance function (HDF) estimation method (Färe et al. 2016) is selected to avoid having to make an arbitrary choice between input-orientation and output-orientation.

Input-oriented and output-oriented efficiency measures are amalgamated in the HDF estimation method i.e., inputs are reduced and outputs are increased simultaneously while efficiency is gauged. The use of HDF *order—α* efficiency estimation in this study provides the distributional flexibility of non-parametric estimators while simultaneously providing traditional statistical features found in parametric estimators, in addition to evading the problem of orientation choice. Also, it can easily be adapted to environmental technologies from the perspective of VRS when undesirable outputs are produced, such as mortality and disease in healthcare systems. Furthermore, the adaptation is seamless when estimating efficiency using the hyperbolic super efficiency ranking approach, a non-linear programming model, developed by (Johnson and McGinnis 2009). This model can also be adapted to measure the Malmquist Productivity Index (MPI) recommended by Zofio and Knox Lovell (2001) when estimating total factor productivity (TFP).

Since DEA has been described in detail elsewhere (Färe et al. 1994b), the basic features of the production function and the DEA linear programming (LP) are delineated briefly in this paper. The number (n) of observed DMUs (SSA countries) each year are presented. Each DMU_j, $j \in J=(1, \ldots, n)$, includes m set of inputs $x_{ij}=x_{1j}, \ldots, x_{mj}$ which can be used to produce s set of outputs $y_{rj}=y_{1j}, \ldots, y_{sj}$. Let λ_j be the jth coefficient of the combination of n possible benchmarks. Consider an aggregating function $g : \mathbb{R}^{2n}_{+1} \rightarrow \mathbb{R}_{+}$, that transforms a vector $\vec{v} = \left(v_1, \ldots, v_n\right)$ into a scalar V, using a set of n coefficient (weights), $\vec{\lambda} = \left(\lambda_1, \ldots, \lambda_n\right)$, and an order w.

Mathematically, $g\left(\vec{v}, \vec{\lambda}, 1\right) = \left(\sum_{j=1}^{n} \lambda_j \cdot \left(v_j\right)^{w}\right)^{1/w} = V$. Assume that $\lambda_j=0, j=1, \ldots, n$ *and* $\sum_{j=1}^{n} \lambda_j = 1$. Given that, g is the so-called generalized mean, and its first order gives the weighted average: $g\left(\vec{v}, \vec{\lambda}, 1\right) = \sum_{j=1}^{n} \lambda_j \cdot v_j$. This is the basis underlying DEA. The distance function uses directional vector to get the technical efficiency following the direction $d_x = \left(d_{x_1}, \ldots, d_{x_i}, \ldots, d_{x_m}\right)$ and $d_y = \left(d_{y_1}, \ldots, d_{y_r}, \ldots, d_{y_s}\right)$, which are vectors with nonnegative entries. Let δ be the distance of the kth DMU to the frontier according to the direction d_x *and* d_y. This means that targets and their relationship with other observations can be rewritten as $x^{*}_{ki} \leq x_{ki} - \delta \cdot d_{x_i}$, $i = 1, \ldots, m$, and $y_{kr}{}^{*} \geq y_{kr} + \delta \cdot d_{yr}$, $r=1, \ldots, s$. The objective is to know the maximum distance δ that maintains feasibility. When δ is optimized, the efficiency score associated to DMU_k can assessed. To construct such a score, we can use the aggregating functions, optimal targets, and observations:

$$\theta = g\left(\frac{x^{*}_{k}}{x_k}, \frac{1}{m} \cdot \vec{1}, 1\right) \Big/ g\left(\frac{y^{*}_{k}}{y_k}, \frac{1}{s} \cdot \vec{1}, 1\right) = \left(1 - \frac{1}{m} \cdot \delta \cdot \sum_{i=1}^{m} \frac{d_{x_i}}{x_{ki}}\right) \Big/ \left(1 - \frac{1}{s} \cdot \delta \cdot \sum_{r=1}^{s} \frac{d_{y_r}}{y_{k_r}}\right) \tag{1}$$

Following (Chambers et al. 1998), we choose $d_{x_i} = x_{k_i}$ and $d_{y_r} = y_{k_r}$ for any $i=1, \ldots, m$ and $r=1, \ldots, s$. Therefore, θ becomes $\theta=(1-\delta)/(1+\delta)$, and if the distance from the kth DMU to the frontier is $\delta=0$ (it is placed on the frontier), then it is technically efficient (i.e., $\theta=1$). The reciprocal is also true. Inefficient DMUs can be identified by $\theta<1$ or its equivalent $\delta>0$.

As stated earlier, some variables take the form of ratios or indexes. Given the convexity assumed by DEA, this kind of variables cannot be directly used by the previous DEA models (Emrouznejad and Amin 2009). However, as claimed by (Olesen et al. 2015), this problem can be surpassed if we disregard convexity and instead take non-convexity as an assumption. This is achieved by simply imposing that coefficients λ_j are Boolean, i.e., $\lambda_j \in \{0, 1\}$, which means that each DMU has one and only one possible benchmark. The linear model becomes a mixed linear programming model which can be solved using computational programming tools or via a simplification resulting from the asymptotic properties of the so-called partial frontiers (detailed below). Consider the transformation of variables (Simar and Vanhems 2012).

$$\left(x'_j, y'_j\right) = \left(\exp\frac{x_j}{d_x}, \exp\frac{y_j}{d_y}\right), \quad j = 1, \dots, n, \tag{2}$$

and the function (Daraio and Simar 2014)

$$w_j = \min\left\{\frac{x'_k}{x'_j}, \frac{y'_j}{x'_k}\right\}, \quad j = 1, \dots, n \tag{3}$$

It can be shown that $\delta = \log$ (max $\{w_j, j = 1, \dots, n\}$). Achieving δ is always a feasible problem because it does not depend on any linear programming tool. By coupling (1) and (3), we obtain the nonconvex efficiency score estimation, θ for DMU k. Note that nonconvex estimators are always consistent even if the production possibility set does exhibit convexity. The converse is not true, though.

The super-efficiency method is a ranking method based on the DEA developed by (Andersen and Petersen 1993) which permits a unit to receive an efficiency score ≥ 1. It has been utilized extensively to rank performance (Wu et al. 2014). However, the conventional super-efficiency models suffer an infeasibility problem. To mitigate this, (Johnson and McGinnis 2009) introduced an alternative non-linear hyperbolic-oriented function to evaluate the efficiency of a DMU relative to a set that does not include the DMU under evaluation. Subsequently, (Färe et al. 2016) developed the HDF estimation method. This is an LP model which can effortlessly be adapted to the super-efficiency model of (Johnson and McGinnis 2009) to calculate hyperbolic-oriented super-efficiency.

It is difficult to determine whether or not an increase or decrease in efficiency each year is owing to a change in technological or technical efficiency. MPI is capable of estimating performance change between two periods (Carboni and Russu 2015). The MPI is used to determine TFP in relation to changes in productivity, technology and efficiency overtime. Using the Malmquist decomposition of (Färe et al. 1994b), it is possible to determine if the performance change is as a result of a change in technological or technical efficiency. The hyperbolic-based Malmquist productivity index developed by (Zofio and Knox Lovell 2001) is used in the current study as it satisfies the criteria of Frisch's circularity test following the adaptation of the HDF model designed by (Färe et al. 2016). Using the hyperbolic Malmquist productivity index, the following decomposition is applied between two periods (s and t) (Färe et al. 1994a)

$$m_0\left(x_s, y_s, x_t, y_t\right) = \Delta T_C\left(x_0^t, y_0^t\right) \cdot \Delta TE_C\left(x_0^s, y_0^s, x_0^t, y_0^t\right) = \left[\frac{d_0^s\left(x_0^t, y_0^t\right)}{d_0^t\left(x_0^t, y_0^t\right)}\right]^2 \cdot \left[\frac{d_0^t\left(x_0^t, y_0^t\right)}{d_0^s\left(x_0^s, y_0^s\right)}\right]^2. \tag{4}$$

The first function measures technological change and the second gauges technical efficiency change. An index of > 1 shows improvement, 1 indicates stagnation and < 1 demonstrates decline (Samut and Cafrı 2016).

2.3 Dynamic Regression Models

Dynamic panel regression estimations are performed to determine the impact of variables regarded as drivers of health system performance on efficiency levels in the second-stage of the analysis. Lagged values of the efficiency series are included as repressors in order to control for the dynamics of the process. In carrying out the panel regression estimations, we identified two potential complications that could significantly distort the outcomes. First, some of the regressors considered in the estimations may be causally related to each other. Separately modeling a regressor without controlling for the effects of the other related regressors on it may cause omitted variable bias. To deal with this potential problem, 5 models are constructed to which the independent variables are added one after the other. The full model is expressed as:

$$eff_{it} = \beta_0 + \beta_1 eff_{t-1} + \beta_2 \ln GDPPC_{it} + \beta_3 URB_{it} + \beta_4 ROL_{it} + \beta_5 GEFF_{it} + \beta_6 PHE_{it} + \varepsilon_{it} \tag{5}$$

where i is the ith country and t is the tth year, $EFF_{t\text{-}1}$ is the lag of efficiency scores, lnGDPPC represented log of GDP per capita, urb indicated the percentage of population living in urban areas, ROL was the rule of law, PHE was public health expenditure as a share of total health expenditure, GEFF represented government effectiveness and ε_{it} represented random noise.

The second potential issue is that reverse causality possibly exists between the dependent and independent variables, especially because of the dynamic nature of our model. Thus, our estimation outcomes are susceptible to endogeneity bias. To deal with this issue, we apply the first and second order lags of all the explanatory variables as instruments. We then estimate each of the six models with Arellano–Bond difference generalized method of moments (GMM) estimator. In addition, Arellano–Bond AR (2) test statistics are used to test for the presence of serial correlation while the Sargan test statistics are used to test for over identifying restrictions. The DEA is conducted using WinQSB® 2 (linear and integer programming), and regression model analysis using Stata® v. 14.

3 Results

The descriptive results of the inputs and outputs applied in the study over the 6-year period are depicted in Table 2. On average, health expenditure per capita increased by 23.50% (4.30% annual growth). The percentage of immunisation for measles, DPT and HepB3 decreased by 2.60, 3.35 and 1.60%, respectively (annual growth of 0.53, 0.68 and 0.33%, respectively). Life expectancy increased by 4.60%, from 57.84 years in 2010 to 60.47 years in 2015 (0.89% annual growth). Infant mortality and maternal mortality decreased by 11.00 and 10.00%, respectively (2.50 and 2.00% annual growth, respectively). Tuberculosis increased by 2.15% (0.43% annual growth). There was a remarkable decrease of 23.00% in the number of new HIV cases recorded. Contrary to the findings of World Malaria Report (2016), a staggering increase in malaria cases was reported, i.e., of 250.00% (28.70% annual growth). Further details on the data are given in (Ibrahim 2018).

Because we are considering some variable as ratios/indexes, the order-α is adopted, which keeps the non-convexity of free disposal hull (FDH). No outliers are detected via order-α with $\alpha = 0.95$ (i.e., assuming that there is a probability of 5% of observing countries dominating the efficient frontier). We pool the sample and create a common frontier for the 6 years to improve the discrimination power of the order-α method. To further improve the discrimination power of the model, the number of variables has to be reduced. One way of dealing with this problem with no significant loss of information is the so-called principal component analysis (PCA) (Gitto and Mancuso 2012) which was also applied in healthcare systems by (Ferreira and Marques 2017). PCA is a very useful technique to narrow down

Table 2 Descriptive statistics on the inputs and outputs of Sub-Saharan Africa healthcare systems

Variables	Role	2010 ($n=31$) Mean (SD)	2011 ($n=34$) Mean (SD)	2012 ($n=35$) Mean (SD)	2013 ($n=35$) Mean (SD)	2014 ($n=38$) Mean (SD)	2015 ($n=37$) Mean (SD)
Health expenditure per capita	Input 1	196.05 (233.90)	178.22 (224.90)	197.70 (249.20)	210.09 (261.70)	237.59 (296.90)	242.17 (298.90)
Immunised measles (%)	Input 2	77.68 (13.84)	79.06 (12.70)	80.11 (12.10)	78.78 (14.60)	76.87 (15.30)	75.65 (16.50)
Immunised DPT (%)	Input 3	79.45 (14.00)	81.62 (13.70)	81.77 (13.90)	81.19 (15.40)	78.71 (18.60)	76.78 (19.00)
Immunised HepB3 (%)	Input 4	78.06 (15.20)	81.53 (13.70)	81.34 (14.20)	81.31 (15.60)	78.82 (18.60)	76.78 (19.00)
Life expectancy (years)	Output 1	57.84 (4.00)	58.77 (3.60)	59.38 (4.00)	59.92 (4.00)	60.30 (4.00)	60.47 (4.00)
IMR	Output 2	58.33 (14.70)	56.26 (13.30)	54.86 (14.90)	53.14 (14.60)	52.08 (14.60)	51.49 (15.20)
MMR	Output 3	539.03 (205.60)	519.09 (184.70)	506.06 (191.20)	496.11 (187.60)	479.84 (192.60)	485.54 (194.90)
Tuberculosis rate (%)	Output 4	55.32 (13.30)	56.82 (12.70)	56.91 (12.20)	57.44 (11.20)	56.39 (12.90)	56.51 (12.90)
Newly infected HIV	Output 5	41,713 (7934)	32,691 (64,115)	29,889 (61,124)	28,172 (56,041)	31,271 (58,849)	31,892 (58,385)
Malaria cases reported	Output 6	638,167 (641,141.)	659,170 (923,073)	1,011,475 (1,218,140)	1,189,118 (1,464,265)	1,926,176 (2,400,225)	2,255,516 (2,747,681)

DPT diphtheria, pertussis (whooping cough), and tetanus, *HepB3* the third dose of hepatitis B containing vaccine, *HIV* human immunodeficiency virus, *IMR* infant mortality rate, *MMR* maternal mortality rate, *SD* standard deviation the number of variables under analysis to remove potential redundancy. By doing so, and using a single component (the first one), you can explain a considerable share of those variables variance. Therefore, reducing the impact of the curse of dimensionality on results and enhancing the method's discriminating power (Ferreira et al. 2018). In this case, the four inputs and the six outputs are aggregated into two variables with no redundancy. $PCA(x)$ and $PCA(y)$ are the first principle components of the four inputs $x_1, \ldots, x_4$ and six outputs $y_1, \ldots, y_6$ respectively. The PCA aggregates the variables that are merged using the largest eigenvalue of the matrixes $[x_1, x_2, x_3, x_4]^T [x_1, x_2, x_3, x_4]$ and $[y_1, y_2, y_3, y_4, y_5, y_6]^T [y_1, y_2, y_3, y_4, y_5, y_6]$. Both $PCA(x)$ and $PCA(y)$ are positively and significantly correlated to their corresponding variables ($P \ll 1\%$). Thus indicating them as good representation of the original data. The procedure explains about 97% of the variance in the corresponding input variables and 96% of the variance for the output variables.

Similar to results from other studies in which efficiency was estimated according to multiple health outcomes, efficiency is found to vary among different countries and across time in the current study. Variations in the performance of SSA healthcare systems during the evaluated period are depicted in Fig. 1. Our findings suggest that 2015 was the best technical efficient year (an average score of 78.1%) and 2010 was the worst performing year (an average score of 70.0%). Only three countries are identified as efficient during the evaluated period, Botswana in 2015, Rwanda in 2014 and 2015, and Tanzania in 2015. About half of the countries evaluated performed below the annual average over the evaluated period, 54.8% in 2010, 52.9% in 2011, 46% in 2012, 52.8% in 2013, 52.6 in 2014 and 54% in 2015. Countries that performed below the efficiency average annually are listed in Table 3. The ranking of each country's healthcare system is provided in Table 4.

The average change in TFP is calculated every two consecutive years within the study period (See Fig. 2). In general, the healthcare systems experienced irregular productivity-related changes. However, TFP increased in the majority of the countries (an index of ≥ 1). The sources of TFP change were decomposed into technological change and technical efficiency change; i.e., the reason for an increase or decrease in productivity between the two periods. The decomposition of TFP is illustrated in Fig. 3. The results suggest that improvements in the productivity of a healthcare system are largely due to technological progress rather than changes in the technical efficiency of the system because an increase in technological progress was demonstrated in the periods of improved productivity i.e., 2010–2011, 2012–2013 and 2014–2015, whereas a decrease in technological progress was associated with periods in which a decline in productivity was observed. Improvements in technical efficiency in 2011–2012 and 2013–2014 did not compensate for the technological

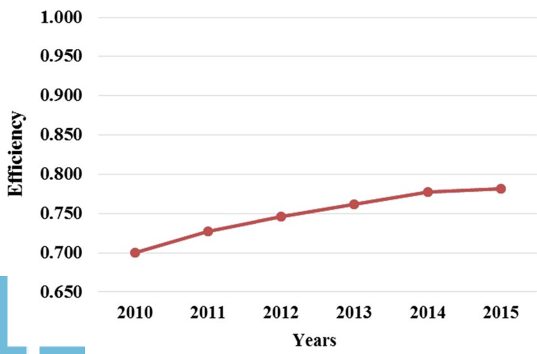

Fig. 1 The average annual efficiency score for healthcare systems in Sub-Saharan Africa

Table 3 Countries in Sub-Saharan Africa whose public health performance was below average

2010	2011	2012	2013	2014	2015
Angola	Angola	Angola	Angola	Angola	Angola
Burkina Faso	Benin	Benin	Benin	Benin	Benin
Burundi	Burkina Faso	Burkina Faso	Burkina Faso	Burkina Faso	Burkina Faso
Chad	Burundi	Burundi	Burundi	Burundi	Burundi
Congo, Dem. Rep.	Cameroon	Central African Rep.	Cameroon	Central African Rep.	Cameroon
Cote d'Ivoire	Chad	Chad	Central African Rep.	Chad	Central African Rep.
Eritrea	Congo, Dem. Rep.	Congo, Dem. Rep.	Chad	Congo, Dem. Rep.	Chad
Guinea	Cote d'Ivoire	Cote d'Ivoire	Congo, Dem. Rep.	Cote d'Ivoire	Congo, Dem. Rep.
Guinea-Bissau	Guinea	Guinea	Cote d'Ivoire	Equatorial Guinea	Cote d'Ivoire
Mali	Guinea-Bissau	Guinea-Bissau	Guinea	Gambia, The	Equatorial Guinea
Mozambique	Liberia	Liberia	Guinea-Bissau	Guinea	Guinea
Niger	Mali	Mali	Liberia	Guinea-Bissau	Mali
Nigeria	Mozambique	Mozambique	Mali	Mali	Mozambique
Swaziland	Niger	Niger	Mozambique	Mozambique	Niger
Togo	Swaziland	Swaziland	Niger	Niger	Nigeria
Uganda	Togo	Togo	Swaziland	Nigeria	Senegal
Zimbabwe	Uganda	Zimbabwe	Togo	Swaziland	Swaziland
	Zimbabwe		Uganda	Togo	Togo
			Zimbabwe	Uganda	Uganda
				Zimbabwe	Zimbabwe

Table 4 The ranking of healthcare systems in Sub-Saharan African countries

Country Name	2010	2011	2012	2013	2014	2015
Angola	17	19	19	20	22	19
Benin	*	18	22	22	25	23
Botswana	9	9	4	3	3	2
Burkina Faso	16	20	20	24	23	20
Burundi	25	28	30	27	31	28
Cameroon	*	29	*	30	*	29
Central African Rep.	*	*	35	36	38	37
Chad	31	34	34	35	37	36
Comoros	*	10	11	12	16	*
Congo, Dem. Rep.	24	27	29	31	29	27
Congo, Rep.	*	12	13	13	12	10
Cote d'Ivoire	30	33	33	34	36	35
Equatorial Guinea	*	*	*	*	33	31
Eritrea	8	3	7	7	7	7
Ethiopia	11	11	12	11	11	12
Gabon	4	*	9	8	8	6
Gambia, The	12	15	16	17	19	17
Ghana	6	7	8	9	9	9
Guinea	21	26	28	28	27	26
Guinea-Bissau	23	25	26	26	30	*
Kenya	1	2	2	4	4	4
Liberia	15	17	18	18	17	16
Madagascar	3	6	6	5	6	5
Malawi	*	13	15	14	14	14
Mali	26	31	31	33	35	33
Mozambique	22	24	27	29	28	25
Namibia	13	14	14	15	13	13
Niger	20	23	25	25	26	24
Nigeria	27	*	*	*	34	32
Rwanda	7	4	1	1	1	3
Senegal	2	1	3	2	5	34
South Africa	14	16	17	16	15	11
Sudan	10	8	10	10	10	8
Swaziland	29	32	32	32	32	30
Tanzania	5	5	5	6	2	1
Togo	18	21	23	21	24	22
Uganda	19	22	21	19	20	18
Zambia	*	*	*	*	18	15
Zimbabwe	28	30	24	23	21	21

* Indicates countries that are excluded from the efficeincy evaluation in that particular year due to data availability

decline that resulted, owing to a decrease in productivity. Although an improvement in technical efficiency was noted in 2012 and 2014, productivity was overshadowed by a decline in technological progress.

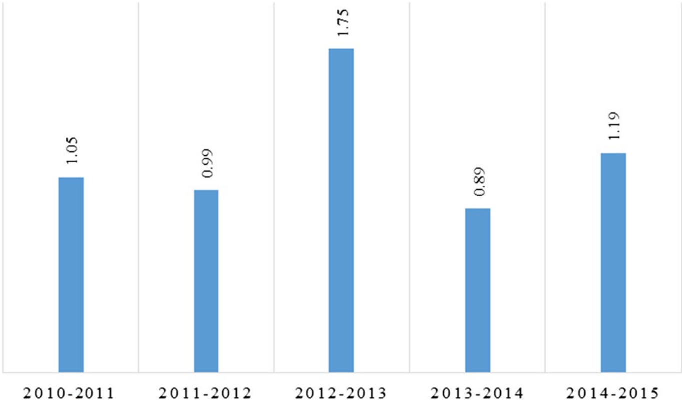

Fig. 2 The changes in average total factor productivity

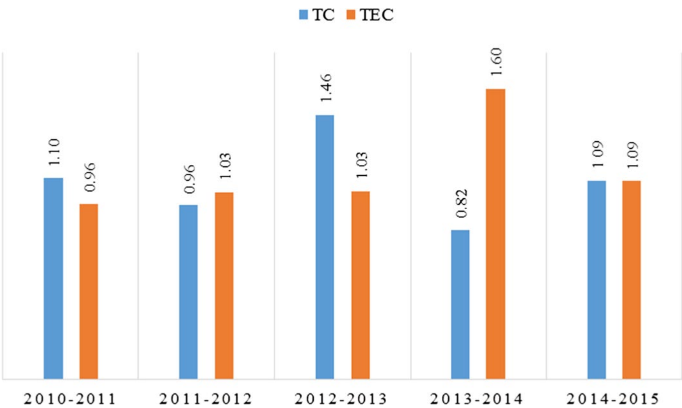

Fig. 3 The decomposition of total factor productivity in healthcare systems in Sub-Saharan Africa, i.e., into technological change and technical efficiency change

Technical efficiency was further decomposed into pure technical efficiency (PTE) and scale efficiency (SE). The average annual PTE and SE of the SSA healthcare systems is depicted in Fig. 4. The results suggest that technical inefficiencies of the healthcare system in SSA countries were influenced to a greater extent by SE than by PTE (Marschall and Flessa 2011). The average SE and PTE was 0.69 and 0.93, respectively, in the study period. The inference is that the inefficiency of healthcare systems in SSA countries is associated with a lack of health infrastructure or underutilisation of the healthcare systems.

The dynamic panel regression estimation results for the five models used to test the influence of GDP per capita, urbanization, public health expenditure as a share of total health expenditure, government effectiveness and the rule of law on healthcare system efficiency are presented in Table 5. Since the reported coefficients in all the models were statistically significant, the focus was on model 5 only. The lagged coefficient of the dependent variable is significantly positive. This is an indication that past achievements in the health sector in terms of sector efficiency has beneficial effects on the current level of efficiency in the health sector. The reported estimates indicated a significant relationship between the

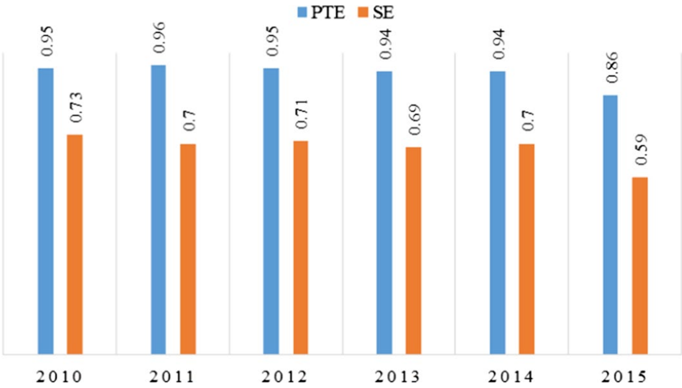

Fig. 4 The decomposition of the technical efficiency of healthcare systems in Sub-Saharan Africa, i.e., into pure technical efficiency and scale efficiency

Table 5 Determinants of the performance of national health systems

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Efficiency (t – 1)	0.329***	0.618***	0.395***	0.983***	0.300***
Log of GDP per capita	1.691**	1.644**	1.535**	1.711**	1.616**
Urbanisation (%)		0.166**	0.170**	0.169**	0.119**
Rule of law			0.201***	0.225***	0.294***
Government effectiveness				0.200***	0.200***
Public health expenditure (% of total health expenditure)					0.085**
Specification tests					
Sargan test statistic	3.476	7.605	2.926	4.846	9.685
P value of Sargan test stat	0.176	0.549	0.570	0.435	0.288
AR(1) test statistic	0.746	0.745	– 0.645	– 0.559	– 0.863
p value of AR(1) test stat	0.456	0.457	0.519	0.576	0.388
AR(2) test statistic	– 0.914	– 0.912	– 1.119	– 1.270	– 0.514
p value of AR(2) test stat	0.352	0.354	0.188	0.111	0.602

Statistical significance is indicated by $*p = < 0.050$, $**p = < 0.010$ and $***p = < 0.001$

socio-economic status of a nation and the efficiency levels of its health system. The positive and significant coefficient for GPD per capita is an indication that higher income levels are associated with higher efficiency. The result shows that a percentage increase in GDP per capita leads to approximately 1.62% rise in efficiency of national health systems. The results also suggest that a significant and positive relationship existed between urbanization and the efficiency of national health systems. It was found in the current study that a percentage point rise in urbanization led to a 0.12 percentage point increase in the efficiency of the national health system. Furthermore, the results show that governance variables positively and significantly influence efficiency of health systems. A percentage-point increase in the rule of law leads to a 0.29 percentage point rise in the efficiency of health systems. Also, a percentage point increase in government effectiveness results in 0.20 percentage point increase in efficiency. The findings also demonstrate that public health expenditure as a share of total health expenditure positively influences efficiency levels, the estimates show that a percentage point rise in public health expenditure leads to a 0.09 percentage point rise in the efficiency of national health systems.

The Sargan test statistics reported for all the five estimations show that the validity of the instruments used in our estimations cannot be rejected. In addition, all the five estimations pass the second order autocorrelation test, an indication that the absence of serial correlation in the error terms cannot be rejected.

4 Discussion and Conclusion

Variations in the efficiency of healthcare systems is observed in the current study following the application of DEA. Underperforming countries can improve productivity by upgrading the technological aspects of their healthcare systems. Technical efficiency can be enhanced by developing SE through infrastructural expansion.

Ensuring the right combination of technical efficiency and productivity optimises the performance of national healthcare systems and helps to actualise the health goals that are set by healthcare system leaders, thus making them more effective overall. The relationship between efficiency, productivity and effectiveness is depicted in Fig. 5, in which the requirement for an effective healthcare system—an improvement in productivity and efficiency—is highlighted. A reduction in productivity is mostly thought to be owing to a decline in technological progress. Technical inefficiency is a result of scale inefficiency rather than PTE. The aim of national healthcare systems is to improve the health status of the population. Healthcare system outputs are represented by health-related MGS. Healthcare system finance and disease prevention measures are considered to be inputs.

It was observed in the current study that the rate of technological change was associated with periodic decline of productivity over time. The adoption of new medication and technologically advanced equipment will facilitate the treatment of difficult and complicated disease, while improving the health outcomes of tuberculosis and malaria patients, as well as reducing infants and maternal mortality. Technological progress, such as process innovation and new treatment methods, expedite improvements in productivity (Li et al. 2014). Increasing the expertise of healthcare workers via employee training requires increased collaboration between governments, universities and hospitals.

The inefficiency of healthcare systems in Sub-Saharan Africa was specifically associated with scale inefficiency in the current study, which corresponds with a lack of health infrastructure or underutilisation of the healthcare systems. This finding was consistent with other studies (Mills 2014) where low- and middle-income countries (i.e., African countries) were demonstrated to have weak healthcare systems. Seventy-five of the countries accounted for 95% of maternal and child mortality. In addition, only a median

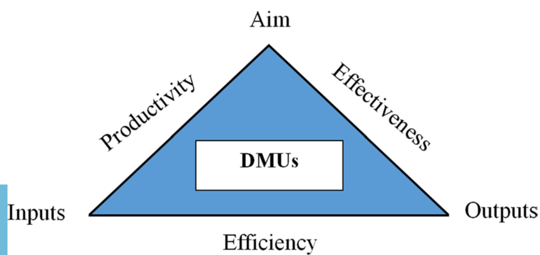

Fig. 5 The relationship between efficiency, productivity and effectiveness

proportion of child births (62%) was attended by a skilled health worker. Similarly, it has been suggested that the capacity of HIV facilities in SSA with regard to managing chronic disease and caring for HIV patients is "untapped" (Di Giorgio et al. 2016). SE can only be maximised if sufficient qualified healthcare practitioners are employed within the healthcare system (Li et al. 2014). These findings support those of the current study on SSA healthcare system inefficiency.

A significant finding of the current study was that although health efficiency correlated strongly with public expenditure on health care, the influence exerted by public expenditure on efficiency was not as powerful as that of governance measures, i.e., the rule of law and government efficacy. This indicates that the volume of resources invested in the healthcare system is not as crucial as the level of efficiency applied to the management of the resources. This finding is in agreement with the results of other research (Rajkumar and Swaroop 2008), specifically that public health expenditure is ineffective in nations that are corrupt and subject to ineffective bureaucracy.

Acknowledgements The authors are indebted to two anonymous referees for their valuable comments for the revision of this paper.

Compliance with Ethical Standards

Conflict of interest All authors declare that they have no conflict of interest.

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