Health System Productivity In Sub-Saharan Africa: Tuberculosis Control In High Burden Countries

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Research Article

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Abstract

Background: 21 of the 30 countries with a high tuberculosis (TB) burden are in Sub-Saharan Africa (SSA). SSA is also home to 74% of all HIV-positive TB patients reported worldwide in 2014. This paper analyses the productivity changes of TB programs and decompose this productivity down into technological change and technical efficiency.

Method: this study was carried out in 16 SSA countries where TB is highly endemic and covers the period 2009-2016. The data is taken from the annual reports of global TB Program. We used the Hicks-Moorsteen index to compute and decompose total factor productivity (TFP), and the β-convergence and σ-convergence tests to check for convergence patterns among SSA countries.

Results: The largest increase in the TFP (35.7%) in 2016 with respect to the base year corresponds to the cutbacks in inputs (9.1%) and a positive change in outputs (0.9%). We found that technological change has been the main driver of the TFP growth, and that increasing technical efficiency may be the first objective in efforts to improve the TFP of TB programs. Our findings support the hypothesis of convergence among SSA countries in the fight against TB. Moreover, corruption was considered as one of the most important determinants of tuberculosis control in SSA countries.

Conclusion: the findings suggest that improving the technical efficiency of TB programs mainly calls for better resource allocation, capacity building in governance and management of programs, improved training of the health providers and stronger prevention policies. An efficient use of funds will arguably reduce the number of tuberculosis cases and TB burden. The Global Fund must closely monitor all the grants in its portfolio and respond decisively and urgently to any instances of corruption.

Key words: Sub-Saharan Africa, tuberculosis, productivity, Hicks-Moorsteen index, technological change, technical efficiency.

Background

"At the core of economics is the concept of efficiency. Microeconomic theory is concerned with allocative efficiency. Empirical evidence has been accumulating that suggests that the problem of allocative efficiency is trivial. Yet it is hard to escape the notion that efficiency in some broad sense is significant" [1]. The quest for technical efficiency in the health sector is closely linked to the theory of X-efficiency developed by Leibenstein [2]. X-efficiency refers to the ability of the firm to increase productivity for a given technology, through improved organization and management as well as enhanced worker motivation [1]. X-efficiency refers to the degree of efficiency maintained by firms under conditions of imperfect competition. "Measuring health care productivity is important as health is a large sector of the economy and with the majority of funding coming from public sources, the outlook for productivity growth is a critical factor in the debate about fiscal sustainability" [2]. It is important to consider how productivity evolves with time. While there is abundant literature on the analysis of productivity of health facilities [3-5], few studies have dealt with the productivity of health programs, such as the global tuberculosis (TB) Program. The Global TB Program aims to advance universal access to TB prevention, care and control, guide the global response to threats, and promote innovation.

TB is one of the top ten causes of death in the world [6]. In 2016, an estimated 10.4 million people worldwide contracted the disease, and that 1.7 million of them died [7]. Low and middle-income countries were the major victims. Over 95% of TB deaths occur in low and middle-income countries [7]. Sub-Saharan Africa (SSA) is among the regions that are highly vulnerable to TB. In 2016, the incidence of TB in this region was estimated at 25%, far higher than in Europe (3%) and America (3%). It is home to 74% of all HIV-positive TB patients reported worldwide in 2014 [6]. 21 out of 30 high TB/HIV burden countries are SSA countries [7].

TB is thus a major public health problem in SSA and deserves special attention [6]. Progress in global TB control is constrained by the lack of effective new tools (diagnostics, drugs and vaccines). The Stop TB Partnership and WHO are promoting the development of better technologies for preventing, and improving the diagnosis and treatment of. To this end, the World Health Organization's (WHO) universal strategy to combat TB and the Sustainable

Development Goals (SDGs) advocate the eradication of TB over the period 2016-2035. The specific targets are to reduce TB deaths by 90% and the incidence of TB by 80% by 2030. This global fight calls for significant mobilization of financial resources. In 2017, funding reached US$6.9 billion in 118 low and middle-income countries, which is more than double the resources available in 2006 [6]. Financial resource mobilization is supported by the fact that the TB strategies implemented are cost-effective [8, 9].

Drug-susceptibility testing (DST) methods generate substantial cost savings in settings of high prevalence of multidrug-resistant tuberculosis [8]. DOTS treatment of cases with negative and extra-pulmonary bacilloscopy, and the DOTS-Plus treatment of multidrug-resistant (MDR) cases have been shown to be cost-effective in developing countries [10, 11]. Furthermore, studies have shown that the administration of bedaquiline to all patients with MDR/RR-TB could increase the success rate [12]. Microscopic Observation Drug Susceptibility (MODS) and Xpert MTB/RIF (Xpert) are cost-effective for diagnosis of pulmonary tuberculosis among HIV patients [13]. Consequently, despite the significant mobilization of financial resources recorded, it is acknowledged that, in order to achieve the SDG targets, substantial additional investments are needed to step up case finding and implement all these interventions on a larger scale [10].

Looking at the TB indicators of SSA as opposed to other regions of the world, one important question comes to mind: would a substantial increase in the funds for TB programs suffice to reduce significantly this disease in SSA by 2030? This question arises in the light of the evidence that health systems and programs in SSA have to contend with weak financial management, inefficient use of resources and inadequate coordination mechanisms to coordinate partner support [14, 15]. Corruption plays a major role in health-care systems in Africa [14]. The returns on health investments of international financial institutions and donors might be very low when mismanagement and dysfunctional structures of health-care systems are not addressed [14]. There is also a lack of organization and of effective management of health services, which coupled with the above-mentioned weaknesses, has led to a situation where 47% of the population have not access to quality health services [14-16]. There are also other important factors such as low levels of awareness about the symptoms, transmission and prevention of tuberculosis and low levels of community involvement [17-18].

In this context, besides cost-effectiveness analyses, it is crucial that in SSA, TB eradication policies be continually geared towards improving the efficiency of TB programs. Improving

the efficiency of TB programs would also free up resources for the development of other sectors that are equally as vital to achieving the SDGs. Therefore, any action aimed at assessing efficiency and productivity changes in the TB sector is an economic policy priority. The main objective of this study is to analyze the productivity of TB programs in SSA. This involves verifying whether or not the productivity of anti-TB programs has improved over time and to decompose this productivity down into its different components. This study is important since it can highlight strengths and weaknesses in current strategies, revealing potential improvements. The results of this study can be used by local authorities and international agencies that fund policies to fight against TB, in order to improve program performance and thereby, ensure value for money. This paper contributes to the enrichment of international research on the analysis of the productivity changes in the SSA health system, adding new empirical evidence to the scarce research to date. In terms of methodology, we use a special index that is rarely used in the health sector, known as the Hicks-Moorsteen Total Factor Productivity Change index (HMTFPC). By using a HMTFPC index, we "overcome the limitations of other indexes. In addition, we use the $\beta-convergence$ and $\sigma-convergence$ tests developed by Barro and Sala-i-Martin [19] to analyze the convergence patterns of productivity change of TB programs in SSA.

Method

The Hicks-Moorsteen total factor productivity change (HMTFPC) index

This section briefly presents the definition and main characteristics of the HMTFPC index. Suppose we analyze the productivity change over two periods represented by t and $t+1$. For period t we define an input vector as $x^t \in R_+^m$ and an output vector as $y^t \in R_+^s$.

We assume that, for each period, we observed n countries with different inputs and outputs represented in period t as (x_j^t, y_j^t) which comes from the reference technology $T^t = \{(x^t, y^t) \in R_+^m \times R_+^s : x^t \, produces \, y^t \}$. In particular, T^t is estimated in Data Envelopment Analysis (DEA) as $T^t = \left\{ (x^t, y^t) \in R_+^m \times R_+^s : \sum_{j=1}^n \lambda_j x_j^t \leq x^t, \sum_{j=1}^n \lambda_j y_j^t \geq y^t, \sum_{j=1}^n \lambda_j = 1, \lambda_j \geq 0 \right\}$ under the assumption of variable returns to scale (VRS) [20] and as

$$T^t = \left\{ (x^t, y^t) \in R_+^m \times R_+^s : \sum_{j=1}^n \lambda_j x_j^t \le x^t, \sum_{j=1}^n \lambda_j y_j^t \ge y^t, \lambda_j \ge 0 \right\}$$ under the assumption of constant

returns to scale (CRS) [21].

The measurement of productivity changes over time using the frontier production method has been the subject of abundant literature with regard to the economic evaluation of decision-making units (DMUs). The productivity index most commonly used in the literature is the Malmquist index [22, 23]. The Malmquist index introduced by Caves et al. [24] was popularized by Fare et al. [25] by providing a decomposition of this index into changes in technological progress and technical efficiency. In its definition, this index is based on the distance function defined by Shephard [26] to represent a technology whose most popular forms are input or output oriented.

The Malmquist output-oriented productivity index [24] is defined as follows:

$$M_I^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D_I^t(x^t, y^t)}{D_I^t(x^{t+1}, y^{t+1})} \frac{D_I^{t+1}(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1})} \right] \quad , \tag{1}$$

Where, $D_I^k(x^h, y^h) = \sup \left\{ \tau : (\frac{x^h}{\tau}, y^h) \in T^k \right\}$ is Shepard's input-oriented distance function calculated from the point $(x^h, y^h), h = t, t+1$ at the frontier of the technology with time $k, k = t, t+1$.

The decomposition of (1) into an efficiency change component and a technological change component is given by:

$$M_I^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_I^t(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1})} \left[\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^{t+1}, y^{t+1})} \frac{D_I^{t+1}}{D_I^t(x^t, y^t)} \right]^{1/2} , \tag{2}$$

A value of $M_I^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ f 1 indicates an increase in productivity over period t to period $t+1$, $M_I^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ p 1 a decrease and $M_I^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = 1$ an unchanged level of productivity.

"Although the Malmquist index can be interpreted as a measure of productivity change over time, it should not be regarded as a total factor productivity (TFP) measure. In a

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multidimensional context, TFP is usually defined as the ratio of an aggregate output to an aggregate input. This definition naturally leads to TFP indices that can be expressed in terms of the ratio of an output quantity index over an input quantity index" [22]. The Malmquist index it is not an adequate total factor productivity (TFP) measure [27, 28]. The Malmquist index generally suffers from several infeasibilities during its application, which are due to its input and output distance functions that could sometimes be undefined. Moreover, "the Malmquist index and its technological change component are also criticized for not fulfilling the determinateness axiom. This drawback is related to the fact that the Shephard distance functions can yield infeasible results when mix periods are evaluated [22]. These problems have been reported in the literature [28, 29].

To solve the problem of infeasibility and interpretation often encountered when using Malmquist indices as a TFP index, Bjurek [29] proposed the *Hicks-Moorsteen Productivity (HMTFPC) index* [30]. The Hicks-Moorsteen Total Factor Productivity (*HMTFPC*) index was introduced with the aim of overcoming all the above weaknesses of the traditional Malmquist index. The HMTFPC index is measured as follows:

$$HM^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{QI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})}{XI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})} = \frac{\left[\dfrac{D_o^t(x^t, y^{t+1})}{D_o^t(x^t, y^t)} \dfrac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^t)}\right]^{1/2}}{\left[\dfrac{D_I^t(x^{t+1}, y^t)}{D_I^t(x^t, y^t)} \dfrac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^t, y^{t+1})}\right]^{1/2}} \quad (3)$$

The characteristics of HMTFPC index generally resolve the limitations of the traditional Malmquist index [22]. First, it can be trivially interpreted as a change in TFP, i.e., the ratio of an aggregate output change index $QI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ to an aggregate input change index $XI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$. Second, this index satisfies deterministic properties under mild conditions [31] since, for all the input distance functions included in (3), it holds that the time period of the reference technology matches the time period of the fixed output quantity and, for all the output distance functions, the period of the reference technology is equal to the period of the fixed input quantity. Third, the HMTFPC index is well-defined even with variable returns to scale [22, 31].

Defining the HMTFPC index has another important advantage in that it is possible to determine the measures of output change, $QI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$, and of input change, $XI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$, which can be useful for a DMU, particularly in the health sector.

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A value of $QI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ f 1 indicates an increase in outputs from period t to period $t+1$, and $QI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ p 1 a decrease. With regard to the change in inputs, the values associated with $XI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ are interpreted in the same way.

For the HMTFPC index, a value of $HM^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ f 1 indicates an increase in TFP, while a value less than a unit indicates a decrease in TFP.

In addition, the HMTFPC index offers several possibilities in terms of its decomposition [32]. O'Donnell [33] recently introduced a general decomposition of the HMTFPC index, which is valid for any 'multiplicatively complete index' [22]:

$$HM^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\frac{TFP^{t+1*}}{TFP^{t*}}\right) \cdot \left(\frac{TFPE^{t+1}}{TFPE^t}\right) \tag{4}$$

Where, $TFP^{k*} = \max\left\{\left[\dfrac{D_o^t(x^t y).D_o^{t+1}(x^{t+1} y)}{D_I^t(xy^t).D_I^{t+1}(xy^{t+1})}\right]^{1/2} : (x,y) \in T^k\right\}$, $k = t, t+1$ represents TFP at the

point of maximum productivity in the period k, and $TFPE* = \dfrac{\left[\dfrac{D_o^t(x^t.y^k).D_o^{t+1}(x^{t+1}.y^k)}{D_I^t(x^k.y^t).D_I^{t+1}(x^k.y^{t+1})}\right]^{1/2}}{TFP^{k*}}$, is

the so-called TFP efficiency and generally represents the measure of DMU performance.

The first component in brackets to the right of equation (4) is interpreted as a measure of the change in the maximum TFP over time, which represents the natural measure of technological change [22]. The second component may be interpreted as a measure of overall efficiency change [33].

In this paper, we use O'Donnel [33] decomposition which is implemented in our empirical analysis using DPIN 3.0 software. Finally, following Aparicio et al. [22] who defined a base period HMTFPC index by fixing a baseline period for technology.

Convergence test

In this section, we present the tests used to analyze the convergence over time of the productivity change index across countries studied. We use the $\beta - convergence$ and $\sigma - convergence$ tests proposed by Barro and Sala-i-Martin [34, 35].

The $\beta-convergence$ establishes a relation between the productivity change index growth rate with respect to the initial period of productivity change. The objective is to verify whether the productivity change index for countries with lower levels of productivity change in the first period grows at a faster rate than for countries with the best initial productivity change index scores [22]. If the β coefficient is negative and statistically significant, convergence is established, otherwise it is a divergence. The regression function [22] used to compute $\beta-convergence$ when analyzing productivity change with the Hicks-Moorsteen index is defined as follows:

$$\ln HM_{i,t} - \ln HM_{i,t-1} = \alpha + \beta \ln HM_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

Where $\ln HM_{i,t}$ is the logarithm of the Hicks-Moorsteen TFPC index of country i at period t; $\ln HM_{i,t-1}$ is the logarithm of the Hicks-Moorsteen TFPC index of country i at period $t-1$; α and β represents the factors to be estimated, and ε_i the error term. By referring to Kumar and Russel [36] and Aparicio et al. [22] we used the generalized least squares (GLS) method to make calculations whenever errors were correlated and/or there was inequality in change.

As for the $\sigma-convergence$, it represents the estimate of the cross-sectional dispersion. It indicates the speed at which a country's productivity change converges with the average productivity change of the sample [22]. The $\sigma-convergence$ is defined as follows [28]:

$$\sigma_t = \sqrt{\frac{\sum_{i=1}^{N}(\ln HM_{i,t} - \mu_t)^2}{N}} \tag{6}$$

Where, N is the total number of countries considered in this study and μ_t is the sample mean of $\ln HM_{i,t}$. There will be $\sigma-convergence$ if standard deviation decreases over time.

Data and variables

Data

The World Health Organization (WHO) has published a global TB report every year since 1997. The purpose of the report is to provide an assessment of the TB epidemic and progress in TB diagnosis, treatment and prevention efforts, as well as an overview of TB-specific

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financing and research. It also discusses the broader agenda of universal health coverage, social protection and other SDGs that have an impact on health. Data were available for 202 countries and territories that account for over 99% of the world's population and TB cases. Our paper covers the period 2009 to 2016, i.e. 8 years. TB data comes from the annual reports of global TB Program. This study covers 16 SSA countries where TB is highly endemic: Angola, Democratic Republic of Congo, Ethiopia, Kenya, Mozambique, Nigeria, South Africa, United Republic of Tanzania, Central African Republic, Congo, Lesotho, Liberia, Namibia, Sierra Leone, Zambia and Zimbabwe. The "high burden" TB countries are those countries that are given the highest priority at global level.

Variables

Given the dearth of studies on the productivity of anti-TB programs, the choice of variables comes only from World Health Organization (WHO) literature. Considering that TB-related deaths among HIV-positive people are officially classified as HIV/AIDS-related deaths in the international classification of diseases, this study focuses only on HIV-negative TB.

Choice of inputs

Care of patients with tuberculosis (TB) starts with a quality assured diagnosis. Successful DOTS expansion, as well as programmatic management of drug-resistant and HIV-associated TB therefore require - at its core - a robust network of TB laboratories with adequate biosafety, modern methods for diagnosis, standard operating procedures and appropriate quality assurance. Nowadays, the WHO recommends rapid tests to determine whether individuals/patients are eligible for the appropriate treatment regimen at lower costs [37]. In some countries, TB diagnostic and follow-up tests are free or fully covered, while in others, patients incur substantial direct and indirect costs [38]. In many low-income countries, access to diagnostic services is difficult particularly in cases of MDR-TB, due to a lack of laboratories [39]. In SSA, the number of laboratories providing TB diagnostic services using smear microscopy and GeneXpert has gradually increased since 2009 [40]. Moreover, depending on the case and the severity of the disease, there are several types and levels of treatment: treatment of new smear-positive cases only under DOTS, smear-positive-plus DOTS-plus treatment, smear-positive-plus treatment of smear-negative cases under DOTS, DOTS treatment of

smear-negative cases plus DOTS-plus standardized second-line drug re-treatment, etc. It is now recognized that in order to eradicate TB, it is important to redouble efforts to mobilize additional resources both nationally and internationally, by gradually increasing the national funding allocation. Resource mobilization from national governments and donor agencies to ensure that these programs are fully funded is essential. SSA countries where TB is highly endemic operate under severe financial constraints and have to compete with other health programs for budget allocations from the government and donors. Because of correlations (covariances) of the variables and the lack of some data for all the countries studied, we used the following inputs: *National TB budget, TB treatment coverage, Number of drug susceptibility testing laboratories for which External Quality Assessment (EQA) was carried out, and the Number of laboratories providing tuberculosis diagnostic services using smear microscopy and GeneXpert.*

Choice of outputs

In this study we use two indicators as outputs: *case fatality ratio (CFR) and TB treatment success rate (new TB cases).*

There are two measures used to assess the proportion of infected individuals with fatal outcomes. The first is infection fatality ratio (IFR), which estimates this proportion of deaths among all infected individuals. The second is case fatality ratio (CFR), which estimates this proportion of deaths among identified confirmed cases. The TB CFR is defined as the proportion of TB patients dying due to TB. The CFR is a key indicator for monitoring progress made in view of the 2020 and 2025 SDG targets. A CFR of 6.5% is required to meet the global 2025 target to reduce deaths and TB cases. This indicator measures the variation of equity in access to TB diagnosis and treatment across countries because, if all TB patients had access to rapid diagnosis and high-quality treatment, the prevalence rate would be low in all countries [6]. With regard to the treatment success rate, WHO considers that high health coverage for appropriate treatment is a fundamental requirement for achieving the targets and objectives of the End TB Strategy. WHO recommends that at least 90% treatment success rate (TSR) for all persons diagnosed with TB and initiated on TB treatment services. Despite this recommendation, substantial shortfalls in TB treatment success are common.

The inputs and outputs we used are defined in the Table 1.

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Table 1 key statistics for inputs and outputs

Results

Descriptive statistics

Table 1 shows that an average of 22.89% of people with TB in the countries studied died from the disease between 2009 and 2016. The SDG targets are to reduce this rate (case fatality ratio) to 10% by 2020 and to 6.5% by 2025. The treatment success rate varies between 23% and 91% over the period studied. The SDGs aim for a treatment success rate of at least 90% by 2030. With regard to inputs, statistics show that significant funding was allocated to national TB programs; over the period studied and depending on the country, the funds allocated to them varied from $1.3 to $475 million on average per year. In addition, some countries do not have drug susceptibility testing laboratories for which External Quality Assessment was carried out. In terms of coverage, the SDGs aim at 90% or more coverage rate by 2010. However, there is still much to be done in this respect, given that over the 2009-2016 period, this rate fluctuated between 23% and 91% on average and per year.

Total factor productivity change (TFPC)

The HMTFPC index was calculated using 2009 as a reference base period and assuming VRS. This index is generally interpreted with respect to the base year [22]. An HMTFPC index greater than or less than 1 indicates an increase or decrease in the TFP, respectively, in comparison to the base year. Table 2 presents the statistics relating to the HMTFPC index and the change in inputs and outputs over time. Percentiles have been used to illustrate the distribution of the index. "This has the advantage of avoiding the biases that top- or bottom-ranking DMUs can cause with respect to mean values" [22].

Table 2 shows that there is a positive TFP index in recent years, although there was a decline in 2014. It is important to note that the largest increase in the TFP (35.7%) in 2016 with respect to the base year corresponds to the cutbacks in inputs (9.1%) and a positive change in outputs (0.9%). In general, the results reveal that during periods of decreasing TFP (8.1%, and 4.3%

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respectively in 2010 and 2011, with respect to the base year) there was an increase in the quantities of inputs used (5.8% and 3.6% in 2010 and 2011 respectively). This result is very interesting as it shows that, despite the increase in resources, the TB programs decreased their mean outcomes achievement.

Table 2 Output-input changes and HMTFPC index

HMTFPC decomposition

An analysis of the two components of TFP, namely, technical efficiency change and technological change shows that technological change has been the main driver of the TFP growth of TB control programs in SSA (Table 3). Furthermore, over the periods 2009-2012 and 2009-2013 characterized by a decline in the TFP, the results reflect a strong improvement in the level of technical efficiency and a decline in technological change. This result suggests that the increase in the level of technical efficiency over some periods was insufficient to increase the TFP. It is therefore important to ensure simultaneous improvement in technical efficiency and technological change.

Table 3 HMTFPC index decomposition

Convergence tests

We carried out a convergence analysis to determine the relative position and distance of productivity change between countries at different time periods.

β − convergence

First, we used the year 2009 as the reference base period and calculated the β-convergence at each period in relation to the base year. Next, we performed the test for each period compared to the previous one, in order to find additional evidence of convergence from one period to another [22]. The results in Table 4 show that the coefficients of β-convergence are negative and significant from one period to another. This points to a converging trend among the countries sampled, that is, the productivity change index for countries with poorer levels of

productivity index in the first period grows faster than for countries with a higher initial productivity change level. Our findings therefore support the hypothesis of convergence among SSA countries in the fight against TB.

Table 4 $\beta-convergence$ coefficients

$\sigma-convergence$

Table 5 presents the 2010-2015 standard deviations of the HMTFPC index for the entire sample and the corresponding p-values for the variance ratio test with the null hypothesis that the ratio of the 2 standard deviations is equal to 1 (as opposed to the 2-sided alternative). In general, and regardless of the period, the results show a non-statistically significant difference between the standard deviations and the base year and from one period to another. Thus, it can be deduced that for the entire sample, the σ convergence occurred between 2010 and 2015.

Table 5 Standard deviation of SSA countries' TFPC

Discussion

The findings of this study show that periods of strong TFP increase correspond to periods of decrease in the quantities of inputs used and increase in outputs achieved, and that periods of TFP decline correspond to increases in the quantities of inputs used. This leads to the hypothesis that TB programs in SSA increase their level of productivity during periods of financial constraints and decrease it during periods of budget surpluses. An efficient use of funds will arguably reduce the number of tuberculosis cases and eventually give a positive impact to the economy. Given the limited resources and a large financial needs to overcome TB, efficiency in using available resources is crucial.

Secondly, according to findings from the decomposition of the HMTFPC index, technological change has been the main driver of growth in TFP over time. Across Africa, affordable smartphones, digital technology, and the connective power of the internet are transforming health delivery. Available technological innovations can solve many of the programmatic and logistical barriers that have hindered TB control efforts for the past years. In addition, the increase in the of technical efficiency observed over certain periods was insufficient to increase

the TFP. This situation can be attributed not only to poor allocation of resources but also and, especially, production that is below the expected outputs. Thus, TB programs still have a long way to go to significantly increase productivity and attain the SDGs.

Several lessons emerge from the computation and decomposition of the HMTFP index. It can be deduced from the results that the threshold for increasing technical efficiency that would trigger and/or enhance the growth of TFP has not yet been reached. Overall, the results suggest that the main difficulty in raising the productivity level of TB programs lies in improving the technical efficiency level. Increasing the technical efficiency of TB programs is therefore the first objective in improving overall factor productivity. Strategies in terms of improved resource allocation, better knowledge of the production process, improved work organization and new investments to increase production capacity and technology are some of the factors likely to significantly enhance the efficiency of these programs.

With regard to resource allocation, which is still the core problem, studies have shown that in developing countries, overdiagnosis could lead to wasted resources (i.e., treatment drugs and manpower to conduct DOTS) [41]. Overdiagnosis and overtreatment due to chest x-rays could lead to an unmanageable burden on resources in poor countries such as those in SSA [42]. Studies have also established a relationship between corruption and outcomes of TB programs [43]. Corruption is considered as one of the main determinants of tuberculosis control in Asia and the Pacific [43]. In the health sector, corruption affects spending on: infrastructure construction, drug procurement, equipment, product quality regulation, services, health centers and health professionals. This negatively affects the health status of the population and the efficiency of health programs [44]. In 2020 report, the Global Fund's Inspector General listed grave misuse of funds in four of the 145 countries which receive grants from the Global Fund; all in SSA [45]. "The Global Fund has suspended relevant grants in Mali and Zambia and terminated another grant in Mali. Special safeguards have been imposed on continuing grants in Djibouti, Mauritania and Mali, meaning that they are subject to particularly close scrutiny and restrictions on cash transfers. These safeguards are also in force in Cote d'Ivoire and Papua New Guinea" [45]. In SSA countries where health systems have to cope with weak financial management and wastage of resources [14, 15], it is important to limit corruption and manage the process of tuberculosis control in order to limit overdiagnosis and overtreatment which have serious financial consequences. The Global Fund must closely monitor all the grants in its portfolio and respond decisively and urgently to any instances of corruption.

For other categories of authors, the less positive results of these programs can be attributed to poor governance [14, 17, 46]; institutional designs and organizational practices influence implementation of the national TB control program. Hence the need to strengthen the governance and management capacity of national TB control programs to ensure robust, responsive and inclusive national anti-TB systems. Governance for strengthening TB control programs in low-resource, high TB burden SSA countries is imperative. Besides, it is important to improve the training of the health providers concerned, through integrated collaborative mechanisms.

Another aspect that is just as important is TB prevention. Despite several interventions, such as the dissemination of TB messages in the media, printing and distribution of information materials, etc., populations in SSA are not sufficiently informed about the disease [17]. Removing stigma and discrimination based on TB status and improving access to TB information including through community involvement, community monitoring and social accountability for early TB diagnosis and improved treatment outcomes. The efficiency of TB programs would also depend on prevention policies aimed at strengthening communication and spreading information on the causes and symptoms of the disease, in order to control and prevent it. These awareness campaigns should target rural areas to encourage the utilization of health care services [18]. Furthermore, there is a need for more effort towards raising awareness among patients with TB about their disease while on treatment.

Finally, the convergence analysis conducted using the β-convergence and σ-convergence tests shows that countries with low productivity growth in the initial period experienced faster and more accelerated increases than the others in the sample. Moreover, these tests reveal significant homogeneity in terms of variation of the TFP.

Despite these important policy implications, this study has some limitations. First, the productivity analysis was done without taking the case mix into consideration in terms of the severity of the cases treated, the quality of care offered, the experience and qualifications of the health personnel, etc. Secondly, we were unable to obtain information on the different types of treatment in order to analyze the productivity of the different lines of treatment in a disaggregated manner. Finally, due to the unavailability of data, we were not able to disaggregate the funding allocated to national TB control programs into its specific components such as prevention, diagnosis, treatment and operating expenses, among others.

Conclusion

The main goal of this paper was to analyze the main drivers of productivity changes of TB programs in SSA. To do this, we applied the Hicks-Moorsteen total factor productivity change index (HMTFPC). "This methodological approach is backed by good theoretical properties, but has hardly ever been used in the health context. The HMTFPC index overcomes the pitfalls of other indexes such as Malmquist index, as it is defined as a ratio of an aggregate output-quantity over an aggregate input-quantity index" [22]. This paper was carried out in 16 SSA countries where TB is highly endemic and covers the period 2009-2016. A number of results were achieved and strategies were proposed to increase the productivity of these programs. The results showed that the main difficulty in stepping up the productivity of anti-TB programs lies in improving their level of technical efficiency, and that technological change was the main source of productivity growth. Increasing the technical efficiency of TB programs is therefore the first objective in improving overall factor productivity. In this regard, it is important to implement strategies to improve resource allocation, strengthen the capacity for governance and management of national TB control programs, improve training for the health providers concerned and bolster prevention policies. The Global Fund must closely monitor all the grants in its portfolio and respond decisively and urgently to any instances of corruption. Finally, governance for strengthening TB control programs in low-resource, high TB burden SSA countries is imperative.

List of abbreviations

CRS: Constant Returns to Scale; CRR: Case Fatality Ratio; DOTS: Directly Observed Therapy short course; DMUs: Decision-Making Units; DST: Drug-Susceptibility Testing; EQA: External Quality Assessment; HMTFPC: Hicks-Moorsteen Total Factor Productivity Change index; IFR: Infection Fatality Ratio; MDR: Multiple Drug Resistance; MODS: Microscopic Observation Drug Susceptibility; SDGs: Sustainable Development Goals; SSA: Sub-Saharan Africa; TB: Tuberculosis; TFP: Total Factor Productivity; TFPC: Total Factor Productivity Change; TSR: Treatment Success Rate; WHO: World Health Organization.

Declarations

Ethics approval and consent to participate

- Not applicable

Consent for publication

- Not applicable

Availability of data and materials

The World Health Organization (WHO) has published a global TB report every year since 1997. All data analyzed during this study comes from the annual reports of global TB Program.

Competing interests

- The authors declare that they have no competing interests

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