Technical Inefficiency of District Hospitals in Côte d'Ivoire: Measurement, Causes and Consequences

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Abstract

The aim of this study is to estimate the level of inefficiency and to identify the causes and consequences of Cote d'Ivoire public hospitals inefficiency. To that effect, we are using the non-parametric Data Envelopment Analysis (DEA) and the double Bootstrap procedures to analyze the data. The analysis of data from the Ministry of Health in Cote d'Ivoire reveals that districts' hospitals are not technically efficient. This situation has a negative impact on hospital output in the country. Thus, the health system is impacted by the inefficiency of districts' hospitals in accommodating the demand of health care. That technical inefficiency remains dependent on environmental factors that constitute an impediment for some of the levers ((*ratio of doctors per capita, malnutrition, average length of stay, geographical access, and correlation Tuberculosis / HIV)* and others (*number of doctors in medical staff*) able to increase hospitals technical efficiency. The outcomes of this study reveal two main stakes: firstly, the need for improvement of hospitals productive efficiency and secondly, the need for a better planning and utilization of the resources allocated to the health sector. Providing adequate responses to these concerns is extremely important for the country's ambition to establish a universal health insurance system and improve the quality of health care services.

Keywords: hospital, technical inefficiency, data envelopment analysis, double bootstrap, tuberculosis/HIV

JEL Classification: C14; D24; I12.

1. Introduction

Authorities in Cote d'Ivoire have chosen health infrastructure decentralization as a way to bring health care closer to the citizens. To this regard, public health care supply was organized into three main clusters. Firstly, we have all the public primary care establishments such as rural and community health care centers that offer curative, preventative, educative and promotional services to patients. Secondly, we have the outpatients and inpatients establishments such as District or Departmental Hospitals that offer consultative care in internal medicine, pediatrics, maternity, and surgery. Finally, we have the specialized centers such as University Teaching Hospitals and Specialized Institutions that provide diagnosis and treatment for complex ailments and also offer research activities. However, the fact remains that hospitals technical facilities are antiquated, and significant inequalities still exist as a result of the primacy given to hospitals in urban areas. Consequently, the Ivorian health care system presents a poor level of performances and a disastrous epidemiological profile (Tiehi, 2012). Moreover, some formerly eradicated diseases such as measles and varicella are resurfacing while other diseases such as cancer, high blood pressure (HBP), diabetes and so on are expanding (MSLS, 2013).

Therefore, the objectives of this study are (i) to estimate the technical performance of districts' hospitals and (ii) to identify the constraints impeding on the development of appropriate health care policies. To that effect, we made the following assumptions: (i) Ivorian public hospitals are technically inefficient and (ii) the performance of a hospital is impacted by factors related to its environment.

This study focuses mainly on districts' hospitals health care supply. This choice is justified firstly by the difference in primary care supply which is open and community base, with undefined competences and a high economic modeling complexity (Amado & Dyson, 2008). Whereas, districts' establishments are more structured with clearly defined competences, receiving patients that cannot be accommodated by primary care centers.

District hospitals regulate access to referral hospitals and are the backbone of the Ivorian health care system. Moreover, the universal health care system project initiated in 2001 but delayed by the military crisis between 2002 and 2011 was reactivated in 2012 with less success. It is clear that those hospitals that make up almost 70% of the public referral health care infrastructures (MSLS, 2013) will define the viability of this social welfare instrument in Côte d'Ivoire.

Pioneering studies from Farrell (1957); Charnes, Cooper and Rhodes (1978) have introduced in the analysis of productive performances the Data Envelopment Analysis (DEA) approach. Initially, a two-step procedure was used in the estimation of efficiency scores: we firstly run the efficiency scores estimation by DEA, then the regression by the truncated likelihood method (a Tobit model) by using the DEA estimated efficiency score as dependent variable to understand the factors affecting the production units efficiency (Scheraga, 2004; Worthington, 2001; Hamilton, 1999; Chilingerian, 1995). However, the high sensitivity of the efficiency scores obtained from the DEA estimation led the authors (Efron, 1979) to use the Bootstrap method to analyze the robustness of those scores while using the Tobit model to capture the impact of the environmental variables. According to Simar and Wilson (2007), that approach is not robust, instead they suggest the double Bootstrap DEA technique. However, the authors (Mujasi et al., 2016; Nedelea et al., 2013; Afonso et al., 2011), continue to use the different approaches concomitantly or alternatively.

The constant use of the DEA approach to estimate the productive frontier in the health care sector is related to its ability to take into account the peculiarities of that sector, such as: (i) the complexity of the technology multi-products and multi-factors, (ii) the absence of variable prices as well for the output and for the input, (iii) the uncertainty in the behavior and the objectives of the hospital sector stakeholders (Coelli et al., 2003). In short, the DEA method is more practical in measuring the efficiency of hospitals that use multiple inputs and produce multiple outputs.

To that effect, Hollinwhorth (2008) observed in a 2006 literature review that more than half of the listed 317 studies on hospital efficiency relied mostly on the DEA method. Studies prior to Hollinwhorth (2008) article reinforced the importance of the DEA method in the analysis of hospitals' performances. As an example, Herrera et Pang (2005) in their study of a sample of 140 developing countries (between 1996 and 2002) observed that the efficiency scores vary between 0.92 and 0.93 for a DEA output-oriented model and 0.84 and 0.87 for a DEA input-oriented model. In the same vein, Dukham (2010) compare the health care systems efficiency for 103 countries and come to the conclusion that African countries are essentially inefficient, even very inefficient.

In sub-Saharan Africa, there is a huge interest in studying production units' performances specially hospitals by using the DEA method. Thus, Ismail (2010) use a DEA with output oriented to estimate the technical efficiency of health care facilities in 15 districts in Sudan. His findings were that 40% of those districts were technically inefficient when returns were constants while they were 33.4% inefficient when returns were variable. Studies from Tlotlego et al. (2010) on 21 hospitals in Botswana were done in the same angle with an average technical efficiency of 74 %. Using the same methodology as Ismail (2010) and Man é (2013) added the Malmquist index in his analysis of the hospitals' technical efficiency in Senegal. He came to the conclusion that hospitals in Senegal had an average technical efficiency of 68% over the period of 2006-2010. Jehu-Appiah et al. (2014) also evaluated the technical efficiency of 128 district hospitals using an output-oriented DEA method with variable returns scale in Ghana. The outcome of that study shows that 76% of hospitals are technically inefficient. In the same dynamic, Ibewuike and Weeks (2014) carried out a comparative study of the technical efficiency of the Gauteng district's public and private hospitals in South Africa and came to the conclusion that private hospitals are technically efficient contrary to the public ones. Public hospitals average technical efficiency scores are comprised between 65% and 76% under the assumption of constant returns scale whereas scores vary between 37% and 60% under the assumption of variable returns scale. Alhassan et al. (2015) analyzed the technical efficiency of certified public and private hospitals in Ghana while Mujasi et al. (2016) evaluated the technical efficiency of 14 regional public referral hospitals and 4 large non-profit private hospitals in Uganda. The outcome of those studies revealed that only 47% of the hospitals in Uganda are technically efficient under the variable returns scale assumption while the average technical efficiency is 91.4% with 56.2% as the lowest score. Recently, Akochi et al. (2017) analyzing the technical efficiency and child health care allocative supply in 17 districts' hospitals in Zambia found through a DEA method that the average technical efficiency of those hospitals is 61,5%. They deducted that the technical efficiency could be corrected through the improvement of the level of education of mothers. Likewise, Diarassouba (2018) analyzed the efficiency of primary health care in Côte d'Ivoire and showed that they have a technically inefficient health care supply with a corrected bias score of 89,8%.

This literature review confirms that the DEA method is the tool mostly used in the estimation of hospitals

technical efficiency. However, the method presents some shortcomings that are corrected by the use of the double Bootstrap DEA method developed by Simar and Wilson (2007). Thus, P érez-Cerceles et al. (2018), using data on European and Central Asian health systems, demonstrate that the DEA Double Bootstrap approach is more effective than the conventional DEA. More recently, Long et al. (2020) in their study get that the potential resource improvement is greater using the DEA Double Bootstrap than that obtained using the classic DEA widely adopted in the aquaculture literature for estimating technical efficiency.

Our study is structured around four sections as follow: after the introduction in the first section, section 2 will take us to the methodology that will present the econometrical modeling and the data to analyze, then the outcomes of the analysis will be discussed in section 3 and finally, section 4 will wrap up the study by presenting the conclusions.

2. Method

The study covers two years of reference (2012 et 2013) and the data are from the database of the Health Ministry of Cote d'Ivoire. The model developed by Simar and Wilson (2007) on the double Bootstrap technique is the one used and applied to the technical efficiency scores obtained from the DEA which principles were already set up in the studies of Farrell (1957) and Charnes, Cooper and Rhodes (1978).

2.1 The Econometrical Model

2.1.1 The DEA Approach

The issue of estimating health care services productive efficiency is not new. Since the landmark study on the nursing services by Nunamaker (1983), numerous publications have been devoted to health care technical efficiency measurement (Achoki et al., 2017; Mujasi et al., 2016; Nedelea et al., 2013...).

In this study, the estimation of the efficiency by the DEA approach goes through the resolution of the K linear programs of each hospital under the assumption of *variable returns to scale (vrs)*. We consider an input-oriented method in the sense that according to the following publications (Kounetas & Papathanassopoulos, 2013; Abbott & Doucouliagos, 2003; Coelli et al., 1998;), hospital has a better control on the input than the output. Moreover, the allocation of capital and labor factors is under the prerogative of the public authority. On the other hand, the output is nearly out of control of the hospital. Thus, given a level of input and a level of output for each hospital, the measure of the technical efficiency is obtained by resolving the DEA linear program defined by Farell (1957):

$$TE_{i}(x, y) = \theta(x, y) = \min \{\theta / \theta \succ 0; \}$$
$$y_{i} \leq \sum_{i=1}^{n} \lambda_{i} y_{i}$$
$$x_{i} \geq \sum_{i=1}^{n} \lambda_{i} x_{i}$$
$$\sum_{i=1}^{n} \lambda_{i} = 1$$
$$\lambda_{i} \geq 0; i = 1, ... n$$

In the DEA linear program, x is the inputs vector, y the outputs vector for each hospital i and λ_i an optimization parameter. By assumption, the technical efficiency *TE* cannot be negative nor grader than 1; in other words, $0 \prec \theta(x, y) \le 1$. The studies admit that *TE* is influenced by environmental variables whose impact needs to be captured. Commonly, the regression of a Tobit model is used to estimate the impact of environmental variables in this second stage (Scheraga, 2004; Wang et al., 2003; Kirjava nen, 1998; Chilingerian, 1995). This approach is not robust in the sense of Simar and Wilson (2007).

2.1.2 The Truncated Regression

The use of the Tobit model for Simar and Wilson (2007) is not appropriate because in reality the estimators are not censored but truncated, they are biased and unpredictable (Battese & Corra, 1977). Moreover, $\hat{\theta}_i$ et ε_i are correlated in series, what make impossible the inference by standard methods. Simar and Wilson (2007) suggest therefore to use the double Bootstrap method (Algorithm 2) to obtain unbiased technical efficiency estimators. Taking into account this critic, we estimate a truncated regression by the maximum likelihood method.

$$\hat{\theta}_i = z_i \beta + \varepsilon_i; \qquad i = 1, \dots r$$

With $\hat{\theta}_i$ being the technical efficiency score in each hospital i, z_i the factors' vectors likely to affect the technical efficiency of the hospital i, β the vectors of parameters and ε_i is the error term identically and

independently distributed.

2.1.3 Double Bootstrap Procedure

The applied procedure in this study follows strictly the Algorithm 2 of Simar and Wilson (2007) which main stages are the following:

- i. Using the initial sample, we will estimate technical efficiency scores under the DEA input oriented: $\hat{\theta}_i(i=1...n)$
- ii. The estimators $\hat{\beta}$ are obtained from a truncated regression $0 \prec \hat{\theta}_i \hat{\beta} z_i + \varepsilon_i \leq 1$, by using $m \leq n$ observations with $\hat{\theta}_i \prec 1$, where $\hat{\theta}_i$ is the hospital technical efficiency i estimated by DEA, ε_i is normally distributed with a truncation to the left at $-z_i\hat{\beta}$ and a truncation to the right at $1 z_i\hat{\beta}$, z_i is the vector of environmental variables that affect the hospital efficiency and $\hat{\beta}$ is the vector of parameters to be estimated.
- iii. By successive iterations (in four stages) $L_1 = 500$ times, we obtain a sample of Bootstrap estimators,

 $B - \{\hat{\theta}_{ib}^*\}_{b=1}^{L_1}; i = 1, \dots n$. We will therefore proceed as follow:

- a. For each i = 1...n, we extract \mathcal{E}_i from the formula $N(0; \sigma^2)$ truncated to the left at $-z_i\hat{\beta}$ and truncated to the right at $1 z_i\hat{\beta}$
- b. Then we calculate the following estimator θ_i^* so that $\theta_i^* = z_i \hat{\beta} + \varepsilon_i$; i = 1, ..., n.
- c. Then we build a bogus sample $(x_i^*; y_i^*)$, with $x_i^* = x_i \text{ et } y_i^* = y_i \hat{\theta}_i / \theta_i^*$.
- d. The new DEA estimator or Bootstrap estimator is calculated from the created bogus sample (x_i^{*}; y_i^{*}); in other words, the variables X et Y are respectively replaced by Y^{*} = {y_i^{*}, i = 1, ..., n} et X^{*} = {X_i^{*}, i = 1, ..., n} in the initial program.
- iv. For each hospital i = 1, ..., n the unbiased estimator $\hat{\theta}_i (i = 1...n)$ is calculated by using the Bootstrap estimator obtained from *B* and the initial estimators $\hat{\theta}_i$.
- v. We then estimate a truncated regression of $\hat{\theta}_i (i = 1...n)$ sur $Z_i (i = 1, ..., n)$ to obtain the estimators \hat{B} .
- vi. By successive iterations (in three stages) $L_2 = 3500$ times, we obtain a sample Bootstrap estimator, $\Delta - \left\{ \hat{B}_{ib}^* \right\}_{b=1}^{L_2}; i = 1, ... n$. To this effect we proceed as follow:
- a. For each i = 1...n, we extract \mathcal{E}_i from the formula $N(0; \hat{\sigma}^2)$ truncated to the left at $-z_i \hat{\beta}$ and truncated to the right at $1 z_i \hat{\beta}$,
- b. Next, we calculate the following estimator θ_i^{**} so that $\theta_i^* = z_i \hat{\beta} + \varepsilon_i$; i = 1, ..., n.
- c. We then estimate a truncated regression of θ_i^{**} sur z_i to obtain the estimators \hat{B}^*
- vii. Finally, we use the Bootstrap estimators of Δ and the initial estimators $\hat{\hat{B}}^*$ to build the confidence intervals for each *B*. The confidence interval for a random B_j is built by finding the values $a_{\frac{q_2}{2}}$ and $b_{\frac{q_2}{2}}$ so that: $P_{rob}(-b^*\frac{q_2}{2} \leq \hat{\beta}_j \hat{\beta}_j \leq -a_{\frac{q_2}{2}}) \approx 1 \alpha$ this allows to obtain an estimated confidence interval $\left[\hat{\beta}_j + a^*\frac{q_2}{2}, \hat{\beta}_j + b^*\frac{q_2}{2}\right]$

The bias in the double Bootstrap model from Simar and Wilson (2007) is non positive and is obtained as follow: $\hat{\theta}_i = \hat{\theta}_i - bias(\hat{\theta}_i)$ with $bias(\hat{\theta}_i) = \left(\frac{1}{L_1}\sum_{b=1}^{L_1}\hat{\theta}_{ib^*}\right) - \hat{\theta}_i$. 2.2 Data

Hollingsworth (2003) has observed the lack of data as a common problem in his comprehensive analysis of 188

studies on the efficiency of health care. The lack of data is more acute in developing countries like Cote d'Ivoire. Also, according to the literature review, we have collected available data relating to the factors of production and products for each of the 65 hospitals in our sample (the total number of districts' hospitals prior to the 2013 reforms that advanced some primary care centers into districts' hospitals). Likewise, the efficiency being linked to some socio-economical (*External environment*) and institutional (*Internal environment*) constraints in the management of the production unit (Leleu & Derveaux, 1997; De Datta et al., 1978), we have therefore collected data on the different constraints.

Thus, we set as inputs the number of beds, used as proxy to the capital factor (Blank & Valdmanis, 2010; Leleu & Derveaux, 1997). The use of the number of beds as proxy to the capital factor helps evade possible biases linked to prices that are regulated by the public health services. The hospital workforce characterizes the labor factor namely the physicians, the nurses, the mid-wives (Flokou et al., 2011) to which we added the other hospital agents. With regard to the outputs, following the path of Romley and Goldman (2011) and Leleu and Derveaux (1997), we measure the number of admissions and the number of hospitalization days which are the indicators of the level of activity for the hospitals, under the assumption that hospitals are paid according to their level of activity.

The efficiency of the health care facility could be influenced by its internal (institutional constraints) and external (people living conditions) environment. The institutional constraints facing the hospital are a vector of factors revealing the quality of health care, namely: the average length of stay of hospitalized patients, and the number of physicians in the hospital. The average length of stay in the hospital is frequently used as an indicator of the efficiency (Leleu & Derveaux, 1997). A short stay reduces the cost per discharge and shift care to hospitalized patients to the less expensive setting for post-acute care. The number of physicians in the hospital translate the density and the specialization of the medical activity in the hospital. However, the socio-economic constraints are translated by four variables indicative of the living conditions of the population and of the governance such as: the ratio of physicians per capita, the geographical accessibility (approximated by the distance to access to the hospital), the malnutrition rate, and the co-infection tuberculosis-HIV. Clearly, remoteness can affect the level of total activity of the hospital insofar as the use of health services is much lower as the population live in remotely far places (Decoupigny et al., 2007; Lucas-Gabrielli et al., 2001). The ratio physician per capita is a health performance indicator and international institutions such as World Health Organization (WHO) and United Nation Development Program (UNDP) use it to appreciate the performance of the health sector of a country. Malnutrition (proportion of children aged 0 to 14) is a proxy that captures the living conditions of the populations (poverty, potable water accessibility...). Those conditions could affect the performances of hospitals as much as more precarious conditions could increase morbidity and cause an increase in the demand of health care beyond the hospital's reaction capacity. The rate of co-infection tuberculosis-HIV characterizes the epidemiological profile of the health district and it is observed that the higher the rate is, the worrying is the health situation as a result the hospital efficiency is affected.

	Variables		Explanation					
Input	Numbers of beds	Bed	Proxy to the capital factor in the hospital					
	Numbers of physicians	Phy						
	Numbers of nurses	Nurs	Indicators hospital workforce or labor factor in the hospital					
	Numbers of midwives	Midw						
	Other agents	Agent						
Output	Admission	Admi	Indicators of hospital activity					
	Hospitalization	Hosp						
Environmental	Average length of stay	Als	Proxys of the institutional constraints					
	Physician ratio in hospital	Phy-r						
	Physician per capita	Phy-cap						
	Geographical accessibility	Dist						
	Malnutrition	Malnut	Proxys of the socio-economic constraints					
	Coinfection Tuberculosis-HIV	t-hiv						

Table 1. Variables specification

Source: Author.

3. Results

3.1 Descriptive Analysis of Variables

In general (Table 2), except the number of hospital beds that decreased relatively, the volume of inputs has known an average increase between 2012 and 2013. This relative increase could be explained by the advancement of some clinics and community health centers into general hospitals (or districts' hospitals). This new provision led to an increase in the number of medical, paramedical, and non-medical staff in the new district hospitals without any tangible improvement in the technical facility. With regard to outputs, we observe that admissions and hospitalizations have increased significantly. Thus, the provision of new medical staff led to an increase in the demand of health services. We can therefore affirm that the establishment of new districts' hospitals and the provision of new medical staff have revealed a demand of health care services not initially known. With regard to the environmental variables, we observe that the ratio physicians per capita, has known a net improvement (going from 23684 to 20893 between 2012 and 2013) even though it is still high. The proportion of physicians in the hospital workforce has also known an increase (going from 41% to 50% between the two periods). Likewise, we observe a sharp drop in malnutrition from 13.17 to 0.69 between 2012 and 2013. We also observe a drop in the joint prevalence of tuberculosis and HIV from 53.29% to 20.98% over the same period. As to the average length of stay and the geographical accessibility, they remain nearly stable between 2012 and 2013.

		20	012						
Variab	oles	Mean	Std, Dev	Min	Max	Mean	Std, Dev	Min	Max
t	Bed	65.72	45.32	8	182	64.09	123.92	5	238
	Phys	17.49	17.80	2	98	20.17	75.89	3	93
Input	Nurs	47.86	29.97	15	178	60.78	83.81	2	264
Ι	Midw	25.84	20.65	2	100	32.93	86.22	5	141
	Agent	10.67	7.72	1	35	13.78	13.23	0	64
ıt	Admi	2439.86	2366.92	20	9396	2982.67	5712.00	50	14171
Output	Hosp	7470.35	7319.77	26	28647	9053.07	15652.13	43	45284
	Als	2.99	0.86	1.30	4.91	2.95	1.57	0.28	12.67
al	Phys-r	41.17	22.10	0	79.03	50.65	10.48	27.27	77.78
nent	Phys-ca	23684.85	15231.94	0	72211	20893.12	12280.28	5134	71939
uuo	Dist	25.41	12.97	0	69.49	26.69	12.45	0	62
Environmental	Malnut.	13.17	19.15	0	66.33	0.69	1.46	0	8
E_1	T-hiv	53.29	88.88	0	639	20.98	8.22	0	46.73

Table 2. Variables statistic description

Source: Author.

3.2 The Efficiency Scores

Estimations by the double Bootstrap DEA method show that the corrected biased technical efficiency scores are respectively 0.617 and 0.563 in 2012 and 2013 (table 3). These scores are lower than the average scores (respectively 0.917 and 0.675) obtained from the estimation of the Bootstrap-DEA method for two periods. This shows that the efficiency scores from the Bootstrap-DEA method (initial scores) are overestimated revealing the fact that they were biased and therefore not robust. This outcome confirms the assertion of Simar and Wilson (2007) that initial scores obtained from the DEA are in general biased around the number one (1).

Generally, these outcomes show that public hospitals are technically non efficient in Cote d'Ivoire and regardless of the estimation method, there is a lost in hospitals technical efficiency between 2012 and 2013. In other words, it would have been possible to obtain an average improvement of 30% and 11.2% respectively in 2012 and 2013 of the utilization of resources allocated to districts' hospitals in Cote d'Ivoire and obtain the same level of health outcome.

		2012	2013			
	$\hat{\theta}$ (VRS)	$\hat{\hat{ heta}}$ (corrected)	$\hat{\theta}$ (VRS)	$\hat{\hat{\theta}}$ (corrected)		
Obs.	65	65	65	65		
Mean	0.9177	0.617	0.6750	0.563		
Std. Dev.	0.1258	0.158	0.2427	0.192		
Min	0.6231	0.241	0.16661	0.135		
Max	1.0000	0.832	1.0000	0.86		

Table 3. Description of efficiency scores

Source: Author.

Table 4 shows that most districts' health establishments in Cote d'Ivoire perform below the reference frontier. Thus, hospitals with low corrected scores are the hospital of Gagnoa (0.241) in 2012 and the one in Agboville (0.135) in 2013. However, the most performing hospitals with the highest scores are the hospital of Sinfra (0.832) in 2012 and the one of Man (0.86) in 2013.

Table 4. Technical efficiency score

Year		2012			2013					
Hospital	$\hat{\hat{\theta}}$ (corrected)	Bias	I.C(95%)		$\hat{\hat{\theta}}$ (corrected)	Bias	I.C(95%)			
Abengourou	0.73	-0.367	1.697	1.098	0.376	-0.409	2.349	3.03		
Abobo nord	0.81	-0.226	1.427	1.062	0.387	-0.424	2.239	2.92		
Abobo sud	0.39	-0.346	2.820	2.319	0.794	-0.188	1.027	1.41		
Aboisso	0.54	-0.356	2.175	1.617	0.488	-0.321	1.818	2.30		
Adiak é	0.432	-0.310	2.538	2.136	0.347	-0.369	2.562	3.22		
Adzop é	0.782	-0.279	1.507	1.160	0.459	-0.310	1.977	2.39		
Agboville	0.482	-0.335	2.335	1.836	0.135	-1.380	6.513	8.45		
Agnibil &rou	0.794	-0.260	1.485	1.127	0.637	-0.203	1.428	1.73		
Akoup é	0.302	-0.380	3.600	2.996	0.274	-0.436	3.281	3.96		
Al ép é	0.722	-0.385	1.715	1.204	0.77	-0.183	1.164	1.44		
Anyama	0.585	-0.314	1.975	1.526	0.725	-0.212	1.212	1.56		
Bangolo	0.763	-0.210	1.495	1.120	0.552	-0.279	1.538	2.07		
B éoumi	0.673	-0.250	1.702	1.225	0.368	-0.370	2.334	3.05		
Biankouma	0.782	-0.279	1.539	1.113	0.467	-0.349	1.826	2.45		
Bingerville	0.82	-0.220	1.394	1.081	0.718	-0.393	1.053	1.76		
Blolequin	0.816	-0.226	1.427	1.068	0.81	-0.234	1.034	1.44		
Bocanda	0.614	-0.247	1.845	1.440	0.70	-0.210	1.226	1.61		
Bondoukou	0.336	-0.474	3.126	2.469	0.78	-0.282	1.106	1.52		
Bongouanou	0.365	-0.550	3.143	2.441	0.58	-0.164	1.548	1.86		
Bouafl é	0.466	-0.356	2.463	1.906	0.847	-0.145	1.044	1.31		
Boundiali	0.42	-0.420	2.725	2.095	0.298	-0.572	2.898	3.86		
Dabakala	0.53	-0.304	2.142	1.629	0.397	-0.450	2.123	2.92		
Dabou	0.753	-0.328	1.626	1.164	0.77	-0.297	1.075	1.56		
Daloa	0.72	-0.273	1.651	1.168	0.724	-0.381	1.071	1.72		
Danan é	0.81	-0.247	1.470	1.088	0.6	-0.230	1.506	1.86		
Daoukro	0.75	-0.228	1.535	1.151	0.64	-0.228	1.404	1.73		
Didievi	0.725	-0.240	1.571	1.175	0.633	-0.329	1.181	1.89		
Dimbokro	0.52	-0.305	2.185	1.738	0.466	-0.286	1.921	2.40		
Divo	0.75	-0.332	1.625	1.031	0.724	-0.222	1.150	1.53		
Gagnoa	0.241	-0.766	4.780	3.615	0.60	-0.350	1.253	1.97		
Grand-Lahou	0.68	-0.205	1.673	1.332	0.48	-0.219	1.840	2.28		
Grand-Bassam	0.38	-0.355	2.901	2.414	0.341	-0.491	2.577	3.24		
Guiglo	0.75	-0.327	1.635	1.043	0.791	-0.264	1.087	1.50		
Issia	0.52	-0.264	2.157	1.737	0.384	-0.391	2.337	2.94		
Jacqueville	0.58	-0.208	1.897	1.532	0.449	-0.279	1.903	2.46		
Katiola	0.68	-0.233	1.681	1.320	0.739	-0.126	1.231	1.46		
Korhogo	0.794	-0.259	1.481	1.050	0.556	-0.322	1.439	2.09		

Kouibly	0.814	-0.228	1.443	1.044	0.50	-0.331	1.685	2.287
Lakota	0.436	-0.331	2.584	2.053	0.318	-0.377	2.777	3.481
Man	0.519	-0.307	2.205	1.682	0.86	-0.162	0.900	1.319
Mankono	0.476	-0.353	2.440	1.717	0.35	-0.328	2.487	3.155
Marcory	0.56	-0.277	2.031	1.581	0.235	-0.676	3.478	4.825
M'Bahiakro	0.80	-0.246	1.478	1.030	0.604	-0.233	1.490	1.859
Minignan	0.746	-0.341	1.647	1.081	0.242	-0.439	3.707	4.493
Odienn é	0.58	-0.314	1.976	1.529	0.83	-0.203	0.897	1.399
Oum é	0.767	-0.204	1.477	1.163	0.65	-0.182	1.380	1.711
Port-bouet	0.759	-0.272	1.544	1.118	0.72	-0.272	1.110	1.640
Sakassou	0.52	-0.339	2.224	1.711	0.35	-0.404	2.443	3.176
San-Pedro	0.75	-0.334	1.641	1.053	0.76	-0.262	1.006	1.560
Sassandra	0.46	-0.379	2.516	1.910	0.815	-0.172	1.048	1.372
S égu éla	0.437	-0.277	2.509	2.055	0.26	-0.539	3.480	4.345
Sikensi	0.812	-0.232	1.438	1.070	0.857	-0.167	1.029	1.327
Sinfra	0.832	-0.192	1.376	1.060	0.782	-0.207	1.142	1.466
Soubr é	0.584	-0.271	1.970	1.468	0.53	-0.286	1.650	2.143
Tabou	0.511	-0.299	2.218	1.744	0.4	-0.430	2.168	2.903
Tanda	0.522	-0.311	2.183	1.727	0.37	-0.399	2.415	3.009
Tengrala	0.752	-0.330	1.625	1.160	0.81	-0.239	1.052	1.467
Tiassal é	0.402	-0.432	2.826	2.236	0.33	-0.447	2.788	3.441
Ti dbissou	0.593	-0.295	1.960	1.476	0.46	-0.262	1.896	2.425
Touba	0.563	-0.271	2.010	1.567	0.71	-0.404	1.076	1.790
Toumodi	0.481	-0.371	2.367	1.831	0.52	-0.254	1.725	2.171
Vavoua	0.487	-0.302	2.267	1.855	0.73	-0.197	1.226	1.536
Yamoussokro	0.739	-0.353	1.657	1.104	0.69	-0.2681	1.210	1.652
Zouan-hounien	0.798	-0.253	1.486	1.097	0.56	-0.348	1.499	2.095
Zu énoula	0.625	-0.190	1.732	1.469	0.54	-0.206	1.660	2.025

Source: Author.

3.3 Determinants of the Technical Efficiency

The estimated scores show that district's hospitals have a technically inefficient health care offer in Cote d'Ivoire. The average biased corrected technical efficiency score of those hospitals is 0,617 in 2012 and 0,563 in 2013. This outcome reveals a technical inefficiency of Ivorian hospitals with a worsening of the situation between 2012 à 2013. This finding confirms the inefficiency of the reforms initiated in the health sector as well as the introduction of the universal health insurance. The technical inefficiency of those establishments is dependent on some environmental factors that can be subdivided into two categories. According to Simar and Wilson (2007), a positive sign of a coefficient induces a positive correlation between the predictor and the level of technical inefficiency of the production unit. Therefore, the environmental factors that are the levers able to increase the technical efficiency of hospitals are the following: ratio of physician per capita, malnutrition, average duration of stay, geographical access, and the correlation Tuberculosis / HIV. However, only the weight of the proportion of physician into the medical workforce can be an impediment.

Thus, we observe that the proportion of physicians in the medical workforce has a negative impact on hospitals' efficiency in 2013 although the variable is non-significant in 2012 (Table 5). This is a coherent outcome showing that the low number of physicians in the medical workforce was a strong impediment to hospitals' efficiency due in part to the heavy load of work. The low ratio of this variable in the post-conflict period and mostly in developing countries, confirms its importance in the hospitals revitalization policies. The more moderately shared physicians' workload is among a large number of the personnel, the high the hospitals' technical efficiency in 2012 and 2013. The recruitments of physicians in the last quarter of 2012 has positively affected the trend and increased the impact of medical staff on the operation and organization of hospitals. In the same vein, malnutrition and the correlation tuberculosis/HIV have a positive and significant influence on the hospitals' technical efficiency. This is due to the fact that actions relating to the fight against malnutrition and sensitization on tuberculosis and HIV have intensified with the increase of hospitals staff. The paramedical staff is focusing more on those actions that were initially done by primary care centers.

				2012			2013							
	$\hat{\hat{eta}}$	I.C	99%	I.C	I.C 95% I.C 90		90%	$\hat{\hat{eta}}$	I.C 99%		I.C 95%		I.C 90%	
Const	1.52	-1.88	4.00	-0.6	3.375	-0.02	3.07	-0.81	-1.67	6.726	-9.75	5.19	-7.67	3.94
Als	0.014	-0.38	0.71	-0.2	0.524	-0.01	0.04	-0.45	-2.97	0.022	-1.55	0.104	-1.23	0.02
Dist.	-0.00	-0.00	0.04	-0.0	0.026	-0.03	0.021	-0.02	-0.20	0.01	-0.11	0.066	-0.09	0.04
Phy-cap	-0.00	-0.00	0.00	-0.01	0.001	-0.00	0.001	-0.0***	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
Phy-r	-0.00	-0.03	0.029	-0.02	0.019	-0.02	0.014	0.1^{***}	0.02	0.53	0.038	0.035	0.052	0.29
Malnut	-0.01	-0.04	0.03	-0.03	0.017	-0.03	0.013	-1.5***	-6.53	-0.02	-4.26	-0.34	-3.30	-0.46
T.hiv	-0.00	-0.01	0.005	-0.01	0.003	-0.00	0.003	-0.1**	-0.05	0.01	-0.32	-0.01	-0.26	-0.02

Table 5. Hospital technical efficiency determinants

Source: Author.

*** = Significant at 1%; ** = Significant at 5%.

4. Conclusion

Our study has set the aim to analyze the productive activity of Cote d'Ivoire district hospitals and understand sources of the technical inefficiency. To that effect. we estimated the technical efficiency of those health facilities. then we analyzed the robustness of efficiency scores obtained and finally we tried to figure out the root causes of the inefficiency. We can easily conclude from the outcome of the analysis that district's hospitals in Cote d'Ivoire are not technically efficient. This fact obviously negatively affects the hospitals' production in the country. In fact, the whole health system is affected because district's hospitals failed to regulate the demand for care. The outcomes of this study come with two main stakes: firstly, improve the hospitals productive efficiency and secondly, the need for a better planning and utilization of the health system resources. Those steps are extremely important if Cote d'Ivoire want to overcome the challenge of poor health care quality and successfully set up its universal health insurance program.

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