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DETERMINANTS OF TECHNICAL EFFICIENCY OF HOSPITALS IN KENYA: 2012-2016

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ABSTRACT

Background: Health care is a basic human right and in the Kenyan constitution, it is the responsibility of the state to provide (GOK., 2010).The government has faced challenges of affordability, quality, availability and timely provision of health care services. Materials and Methods: The study used output oriented VRS_TE DEA model. In estimating the determinants, random effect panel regression model was used. The variables were; log of size, bed occupancy, catchment population, teaching status, average length of stay as independent variables and technical inefficiency as the dependent variable. The data was collected from the hospitals' published data, and government statistics. Results: There was a general decline in efficiency between 2012 and 2016. VRS_TE (0.9012) was higher than CRS_TE (0.8042). The hospitals were heterogeneous in their operations. There was no hospital which was consistently efficient throughout the period. The average length of stay had significant negative relation with technical efficiency. Conclusion: Technical efficiency is negatively related with the average length of hospital stay. The hospitals should reduce the length of hospital stay through early discharge for stable cases and institute home care for follow-up and to handle the non-life threatening cases through home care.

Contribution/Originality: This study contributes to the existing literature by using random effect model to estimate the determinants of technical efficiency. The primary contribution of this study is to demonstrate that devolution of health services positively affected health outputs and that average length of stay had significant negative effect on technical efficiency.

1. BACKGROUND

Health care is a basic human right and in the Kenyan constitution its provision is the responsibility of the state (GOK., 2010). Where the state cannot adequately provide for it for reasons of fragile health system and associated financing problems, the poor and vulnerable have borne the greatest burden of the health care provision. The health care system in Kenya consists of 9000 health facilities mainly divided into private (Faith based, Non-governmental organizations, Trusts, Foundations and other private for profit) and public (government & Parastatals). The government oversees the running of 42 percent of health facilities (3780) the private sector for profit operates 15 percent (1350) and the not-for profit non-governmental organizations 43 percent (3870) of the health facilities respectively. The entire private sector including the not for profit organizations constitutes 58 percent and employs 50 percent of the total health professionals in Kenya (KDH, 2014). Most of these private health facilities are beyond the financial and location reach of the 70 percent of the poor population residing in urban informal settlements and rural areas as they either charge market or cost recovery fee (KDH, 2014). The main health service provider for 70 percent of Kenyans remain the underfunded, understaffed, and ill equipped public health facilities (African Health Observer-AHWO, 2009). The distribution and macro-organization of the health facilities in Kenya follows from the Health Sector Strategic Plan (GOK, 2014). Under this policy framework, the health sector operates under a hierarchical system (World Bank, 2014). The health posts are at the bottom of the pyramid, followed by the Community dispensaries, which are the largest in number and the entry point into the health system. These are followed by the Health Centers, Health clinics and the District and Sub-District Hospitals and the provincial hospitals at the apex of the provincial administration of health care. At the top of the pyramid are the five national teaching and referral hospitals; Kenyatta National Hospital, Moi Teaching and Referral Hospital, National Spinal Injury Hospital, Mathari National Teaching & Referral Hospital, and Kenyatta University Teaching and Referral Hospital. The former eight provincial administrative units were responsible for delivering all government services including health. With the devolved system of government in 2013, health services were devolved to the counties giving rise to a slight reorganization where the district and provincial hospitals were elevated to county referral hospitals and among other administrative and financing reorganizations (Chuma & Okungu, 2011; MOH, 2014).

This paper addresses the problem of inadequate availability of affordable, accessible, appropriate and timely health care to the over 70 percent of middle and low income Kenyans not covered by any medical schemes. This population solely depend on publicly provided health care services. The public sector controls 42 percent of the health facilities and employs 50 percent of the health professionals. These public health facilities are underfunded, heavily dependent on donor support, understaffed with inadequate health supplies, and equipment. In the recent past, this sector has witnessed several industrial disputes, go slows and strikes concerning scheme and terms of service. Devolution was intended to take services closer to the people. However, due to the teething problems, this transition has had several administrative, financing and perception challenges.

Technical efficiency is the use of inputs to obtain maximum possible output for a given technology set (Farrell, 1957). Technical efficiency can be input-oriented meaning using minimum level of inputs to produce a stipulated level of output for a given technology. This approach is also known as the "input-saving" approach (Farrell, 1957). In this approach, output levels remain unchanged while input quantities are reduced proportionately until the efficiency frontier is reached (Farrell, 1957). On the other hand, the output-oriented approach also known as "output-augmenting" approach, seeks to address maximization of output from a given set of inputs and technology. As the input bundle remains unchanged, the output level increase until the efficiency frontier is reached (Farrell, 1957). In this context, firms' efficiency is measured relative to an estimated efficiency frontier (Charness, Cooper, & Rhodes, 1978).The objective of this study is to analyze the determinants of technical efficiency of the county referral hospitals in the Lake Region Economic Block of Kenya for the period 2012-2016. The technical efficiency scores are estimated using the output-oriented variable returns to scale DEA model (Banker, Charnes, & Cooper, 1984). The relationship between technical efficiency and its determinants was estimated by the random effect panel regression model. The period 2012-2016 was chosen as it marks the transition from the centralized provision of health care services to the devolved provision of health care services as provided under the 2010 constitution (GOK., 2010). The study purposively sampled fourteen (14) county referral hospitals (level 4 and 5) out of the 47 county referral hospitals. The purpose was to compare the hospitals in the counties forming the Lake Region Economic Block (LREB). This is due to the fact that the region has shared health and other development goals for shared prosperity. The study used hospital and government published date from individual hospitals' published records and the economic Survey The paper is organized as follows: section 1 discusses the background, while section 2 materials and methods. Section 3 and 4 presents the results and limitations respectively, while 5 is the conclusion.

2. MATERIALS AND METHOD

2.1. Methods

The study of efficiency is based on the theory of production. This theory postulates that a production unit in its production process transforms a set of inputs $x \equiv (x_1,...,x_n)$ into a set of output $y \equiv (y_1,...,y_n)$, given a technology set $T = \{(X^t, Y^t) : X^t \text{ can produce } Y^t)\}$ Where $X^t = (x_1, x_2,...x_n) \in \Re_t^n)$ denotes a non-negative n x1 vector of inputs and $Y^t = (y_1, y_2,..., y_n) \in \Re_t^m$ denotes a non-negative m x1 vector of outputs (Jehle & Reny, 2011) . Such production technology set T can be expressed using two equivalent forms: the input requirement set, $L(Y) = \{x : (x, y) \in T)\}$ and the output requirement set (Jehle & Reny, 2011). This transformation is achieved through a production function $f(x)$. This function defines the maximum output obtainable from a given set of inputs (Coelli, Rao, O'Donnell, & Battese, 2005). This function $f(x)$, defines the theoretical limit on the possible values of the output. Given the firm's production plan as (y^0, x^0) this plan is considered to be technically efficient if $y^0 = f(x^0)$ (Coelli et al., 2005).

2.2. The Models

Technical efficiency is estimated using the output oriented variable returns to scale model of Banker et al. (1984). This model is given as: $MinQ_h = \sum_{i=1}^{m} v_i x_{i0} - \mu_0$

(i) Subject to: $\sum_{I=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - u_0 \geq 0$ (i.e all DMUs lie on or below the frontier)

$$\sum_{r=1}^{s} u_r y_{r0} = 1$$

Minimize the inputs used in producing a given level of output, subject to the difference between the weighted sum of inputs and outputs being greater or equal to zero.

$u_r, v_i \geq 0$, and μ_0 is free in sign. (Cooper, Seiford, & Tone, 2006).

y_{rj} (r =1,…,s) is the observed amount of, r^{th} output produced by the, j^{th} hospital, u_r is the weight attached to output y, x_{ij} (i =1,…,m) is the observed amount of the, i^{th} input for the, j^{th} hospital, and v_i is the weight attached to the inputs, *i*, n is the number of hospitals in the sample and, *h*, is the hospital being evaluated in the set of, j=1,…*n*. hospitals. This relative hospital efficiency is bounded between 0 (completely inefficient) and 1 (technically efficient) i.e. $0 \leq \theta_h \leq 1$. The relationship between the efficiency/inefficiency of the hospitals and its determinants is estimated using the random effect (RE) panel regression model given as:

$$y_{it} = \beta_j \sum_{j=2}^{k} x_{jit} + \alpha_i + \delta_t + \mu_{it}$$

(ii). (Baltagi, 2013) Technical inefficiency of the hospital at a point in time is a function of a vector of observed explanatory variables (determinants), the hospital specific effect, the individual time effect and the error component (unobserved individual cross section and time series errors).

α_i are assumed to be random variables rather than fixed constants, thus the variations across entities are assumed to be random and uncorrelated with the predictor or independent variables included in the model (Pesaran, 2015). If the μ_i can be assumed to be random, then the loss of degrees of freedom due to too many parameters in the fixed effect model is avoidable. Therefore the μ_i ~IID $(0, \sigma_\mu^2)$, (v_{it} ~IID $(0, \sigma_v^2)$, and the μ_i are independent of the v_{it} . The x_{it} are independent of the μ_i and the v_{it} for all i & t (Baltagi, 2013). δ_t , is the individual time effect, α_i is the entities specific effect, x_{jit} is k vector of explanatory variables, β_i are the slope coefficient of the explanatory variables and μ_{it} is the combined cross section and time series error component. With these assumptions, the RE allows the time-invariant variables to play a role as explanatory variables (Baltagi, 2013).

The estimated empirical panel regression equation is given as:

$$Ineff = \alpha_i + \beta_1 LSIZE + \beta_2 TEASTAT + \beta_3 BOR + \beta_4 ALOS + \beta_5 CPOP + \delta_t + \mu_{it} \qquad (3)$$

Technical inefficiency depends on the individual hospital effect log of bed size, teaching status, bed occupancy rate, average length of stay, catchment population , individual hospital time dependent effect and the error term.

LSIZE is the natural log of beds taken as proxy for hospital size, TEASTAT is a dummy variable taking the value of 1 if the hospital is a teaching hospital and 0 if not, BOR is bed occupancy rate, ALOS is the average length of stay in a hospital as an in-patient, and CPOP is the hospitals catchment population. $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the coefficients to be estimated, *i* represents the particular hospital, *t*, represents time, α_i is the individual hospitals' fixed effect, δ_t is the time effect and μ_{it} is the combined cross section and time series error component (Baltagi, 2013).

2.3. Variable Description and Measurements

Size is measured as the log of total beds in a hospital. Teaching status as a variable is a measure of whether the hospital serves as a teaching hospital. It is measured as a binary variable taking the value one (1) if the hospital is a teaching hospital and zero (0) if not. Teaching hospitals are therefore characterized as large with multiplicity of departments for teaching purpose. Teaching status of the hospital affects efficiency through the various professionals and teaching departments. This could have a positive effect on efficiency if this status improves the facility, equipment and staff composition of the hospital. It could however, have a negative effect on efficiency if it leads to over focus on teaching at the expense of patients. Besides in the absence of adequate equipment, and professionals, the case loads could overwhelm the system thus leading to negative effect. Average length of stay (ALOS) measures the average number of days a patient stays in hospital in a given period (total inpatient days of care/discharges +deaths). This measure could be low due to early discharges as a result of patients' inability to pay or pressure from those on admission waiting list or long due to delayed settlements of hospital charges. This measure could be affected also by the hospitals case mix. Bed occupancy rate (BOR) is a measure of the utilization of the available bed capacity and is expected to positively affect efficiency. It defines the percentage of bed occupancy per given period of time (a year). This measure may give misleading results in cases where 'floor' admissions exist and the hospital registers more than 100 percent occupancy. Catchment population is composite external environmental variable comprising of population density, poverty, health indicators, and service utilization. In most of the reviewed studies, it is aggregated as a single variable. This variable determines the health care needs and the case mix. The larger the population, the more complex are the health care needs, and the greater is the pressure on given hospital resources. Hence catchment population was expected to be negatively correlated with efficiency (Chang, 1998).

Table 1 summarizes the empirical literature on the determinants of technical efficiency. The purpose of this summary is to identify the geographical spread of the studies, the methodology and the findings so as to identify the gap to be filled by the current study.

Table-1. Empirical literature review on determinants of technical efficiency.

Author	Country	Method	Findings
Asbu, Masri, and Naboulsi (2020)	South Africa	Tobit Regression	Positive relationship between size and technical efficiency
Cheng, Tao, and Cai (2015)	China	Tobit Regression	Size, and average length of stay were reported to be negatively correlated with technical efficiency.
Mwihia, M'imunya, Mwabu, Kioko, and Estambale (2016)	Kenya	Tobit Regression	Size and average length of stay are negatively correlated with technical efficiency
Ali., Debela, and Bamud (2017)	Ethiopia	Tobit Regression	Negative correlation between technical efficiency and teaching status
Kirigia. and Asbu (2013)	Eritrea	Tobit Regression	Positive relationship between technical efficiency and average length of stay
Dutta, Bandyopadhyay, and Ghose (2014)	India	Two-stage generalized least square Regression	Negative relationship between technical efficiency and average length of stay
Xenos, Nektarios, Constantopoulos, and Yfantopoulos (2016)	Greece	Tobit Regression	Negative relationship between average length of stay, bed occupancy rate and technical efficiency
Andrews (2020)	New Zealand	Truncated Regression	Negative relationship between technical efficiency and average length of stay
Mujasi, Asbu, and Puig-Junoy (2016)	Uganda	Tobit Regression	Positive correlation between bed occupancy rate and technical efficiency
Ahmed et al. (2019)	Bangladesh	Tobit Regression	Positive correlation between bed occupancy rate and technical efficiency
Jing, Xu, Lai, Mahmoudi, and Fang (2020)	China	Tobit Regression	Positive correlation between bed occupancy rate and technical efficiency
Bobo et al. (2018)	Ethiopia	Tobit Regression	Positive relationship between catchment population and technical efficiency

The reviewed studies used largely the Tobit regression model, however few of them used truncated regression and two stage generalized least square regression. These empirical studies reviewed showed efficiency scores clustered in the range of 0.4 to 1. The efficiency/ inefficiency score is located between a maximum (1) and a minimum (0), hence it is not a binary variable. OLS would be inappropriate where there is panel effect (Biorn, 2017). There have been no documented studies in Kenya, comparing the efficiency of the county referral hospitals. Regional benchmarking and resource sharing would be the way forward in public health provision given that health resources are scarce and the counties are exclusively zoned off from each other. This gap has no documented study to provide the much needed empirical evidence necessary to inform policy. This paper fills this gap by estimating the relationship between hospital efficiency and its determinants in Kenya. The current study used the panel regression estimated by GLS and the ML due to the presence of the panel effect, and that fact that efficiency lies in the range 0 to 1.

2.4. The Conceptual Framework

The conceptual framework in Figure 1 shows the relationship between the inputs, the production process, and the outcomes. The production process is an integrative system of these component parts.

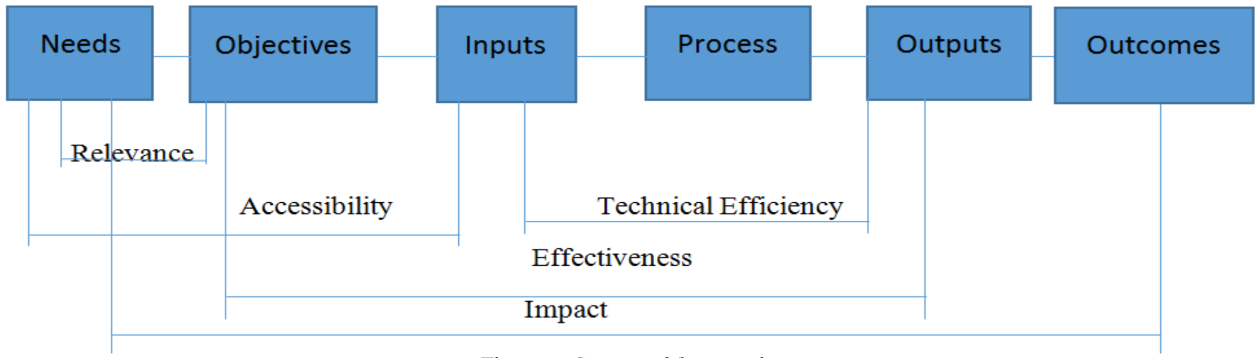

Figure-1. Conceptual framework.

Source: Modified from Sloan and Hsieh (2017).

Health production is best described by the process in Figure 1 which shows that production is an interaction of different parts put together to achieve an overall health systems' goal of a healthy population free from disease and its burdens (Sloan & Hsieh, 2017). The analysis of technical efficiency looks at a component part of this whole process as it relates inputs to outputs through a production process defined by a given technology set and the determinants of this efficiency to inform efficiency enhancement plans.

3. RESULTS

3.1. Descriptive Statistics

Tables 2 consolidates the descriptive statistics of the variable used in the estimation of technical efficiency and its determinants. Average length of stay is positively skewed with a negative kurtosis. Bed occupancy rate is negatively skewed with positive kurtosis. Catchment population is positively skewed and has positive kurtosis. The above measures of skewness and kurtosis fall within the acceptable limits of +2 and -2 (Ryu, 2011).

The estimated efficiency results show that there were no hospitals which were continuously efficient throughout the entire five years. This means that, there were no distinguishable technological leaders in the sampled hospitals. The spread of new technology therefore occurred smoothly and without a definite pattern across hospitals. The results also show that the annual mean TE_VRS scores (0.90121) are higher than the TE_CRS scores (0.80436). This difference arises because CRS compares the efficiency of each hospital in relation to all the efficient hospitals in the sample, whereas the VRS compares the efficiency of each hospital in relation to only the hospitals in the sample which are operating at the same scale as the focal hospital. The VRS computes efficiency with scale efficiency, while CRS scores may be masked by scale inefficiencies. These results of the TE_VRS are similar to those of Kirigia, Emrouznejad, and Sambo (2002) which reported technical efficiency of 0.936. The differences in the results with other studies, in Kenya, could be due to the fact that the reviewed studies focused on Specific County and on the lower level health facilities (clinics) which were also small in size.

Table-2. Descriptive statistics.

Descriptive Statistics										
	N	Min.	Max.	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
BEDS	70	124	365	218.37	9.257	77.448	.716	.287	-.746	.566
Outpatients	70	9600	46375	17788.29	1096.545	9174.357	1.968	.287	2.883	.566
Medical Staff	70	53	350	139.86	9.897	82.804	1.359	.287	0.399	.566
Deliveries	70	1108	4068	2399.87	108.076	904.230	.191	.287	-0.405	.566
Bed Occupancy Rate	70	.6287	.9897	0.8799	0.0103	0.0859	-.784	.287	.296	.566
Hospital Size	70	2.0934	2.5623	2.3140	0.0178	0.1487	.297	.287	-1.060	.566
Average Length	70	4	13	8.16	.263	2.204	.004	.287	-.734	.566
Catchment Pop	70	585582	187268	1028212	37639	314909	1.110	0.287	0.852	0.566
Inefficiency= (1/TE scores)-1	70	0.0000	0.47	0.1242	0.0122	0.1017	0.867	0.287	0.877	0.566
VRS_TE	70	0.68	1	0.8978	0.0091	0.0764	-0.459	0.287	0.224	0.566

3.2. Summary of Mean Efficiency Scores

Table-3. Five year mean Efficiency and Output Slacks per Hospital for 2012-2016.

Hospital	CRS_TE	VRS_TE	SCALE
1	0.8407	0.84504	0.9949
2	0.96694	0.97102	0.98712
3	0.9292	0.93876	0.98966
4	0.74126	0.89052	0.8279
5	0.6875	0.96118	0.71412
6	0.8111	0.86526	0.98278
7	0.50886	0.8652	0.5944
8	0.66562	0.92626	0.71752
9	0.93934	0.9523	0.98606
10	0.9247	0.92666	0.99784
11	0.70544	0.81582	0.8638
12	0.81948	0.88354	0.9298
13	0.76582	0.81996	0.92568
14	0.95508	0.95548	0.99958
Mean	0.80436	0.90121	0.89365

Figure 2 shows the distribution of the annual mean across the county referral hospitals for the period 2012-2016.

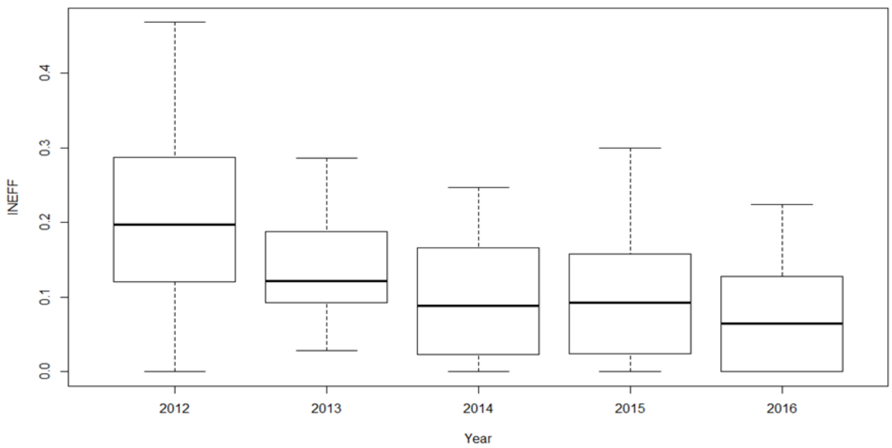

Figure-2. Box plot of annual inefficiency across hospitals.

Figure 2 is a box plot of the above trends of inefficiency across time (2012-2016). It is a summary of the annual inefficiency across the fourteen county referral hospitals. It shows that there was overall skewness in efficiency scores and a general decline in inefficiency where the mean inefficiency in 2016 was below that of 2012, 2013, 2014 and 2015 and a general increase in skewness of inefficiency in 2015. 2015 marked the expiry of the mandate of the transition authority and the commencement of the full devolution of the health care services to the county governments. There were issues of staff takeover and the general apprehension of the medical professionals regarding the ability of the county governments to handle health care provision. There were also pending issues of staff terms and conditions of service which were carried over from the central government. These challenges were to be handled by county governments with little experience in managing health services and resource constrained as most of the resources were disbursed from the central government, with challenges of timely disbursements. These issues continued into 2016, which witnessed a nationwide industrial unrest.

3.3. Correlation Analysis

Table 4 shows the Pearson correlation matrix between the variables used in determining how hospital and external environmental variables affect efficiency

Table-4. Pearson correlation matrix.

Variables	TEASTAT	BOR	LSIZE	ALOS	CPOP	INEFF
TEASTAT	1.0000					
BOR	0.439** (0.000)	1.0000				
LSIZE	0.686** (0.000)	0.418** (0.000)	1.0000			
ALOS	-0.015 (0.9000)	-0.262* (0.028)	0.065 (0.594)	1.0000		
CPOP	0.582** (0.000)	0.299* (0.012)	0.572** (0.000)	-0.065 (0.594)	1.0000	
INEFF	-0.154 (0.203)	-0.058 (0.632)	0.017 (0.889)	0.446** (0.000)	-0.273* (0.022)	1.0000

Note: ** Correlation significant at the 0.01 level, * correlation significant at the 0.05 level (2-tailed).

The matrix shows that there is no statistically significant correlation between inefficiency and teaching status, bed occupancy rates, hospital size, and captive population. Average length of stay had significant positive correlation with inefficiency while CPOP had significant negative correlation with inefficiency. In terms of teaching status and other independent variables, there is significantly positively correlation with, bed occupancy rates, hospital size, and captive population. Bed occupancy rates are positively and significantly correlated with hospital size and captive population. The rates are significantly negatively correlated with average length of stay. Size is significantly positively correlated with captive population while the relationship with ALOS is not statistically significant. Average length of stay has insignificant correlation with captive population.

Table 5 shows the variance inflation factor and tolerance for multi-collinearity analysis.

Table-5. Multi-collinearity analysis.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.450	.241		-1.872	.066		
	TEASTAT	-.050	.041	-.188	-1.217	.228	.454	2.204
	BOR	-.159	.146	-.134	-1.084	.283	.707	1.415
	LSIZE	.165	.105	.241	1.564	.123	.455	2.197
	ALOS	.020	.005	.444	4.016	.000	.885	1.129
	CPOP	-1.017E-007	.000	-.315	-2.345	.022	.599	1.670
a. Dependent Variable: Inefficiency.								

The results from Table 5 show that multi-collinearity is not a serious problem as the variance inflation factor is below the threshold of 5.

The Augmented Dickey-Fuller test for unit root showed that all the variables are stationary in levels. The results are: Dickey-Fuller = 4.3073, Lag order=2, p-value=0.01. Given this result, the study therefore estimated the model in levels, except size of hospital which is proxied by the natural logarithm of bed size.

Table 6 Presents the model robustness tests which are essential before the model can be used for estimations.

Table-6. Estimation tests.

Test	*Test Statistics*
ADF Test (Stationarity)	ADF=-4.3073, Lag order=2, p-value =0.01
Hauseman Test	Chi^2(1)=0.40466, p-value=0.5247
Breusch-Godfrey/Wooldridge Test (Autocorrelation)	Chi^2 (4)=9.7067, p-value=0.04567
Breusch-Pagan Lagrange Multiplier Test (for cross sectional dependence)	Chi^2 (1)=33.628, p-value=6.72e-09
Breusch-Pagan/Cook-Weisberg test (heteroskedasticity)	Chi^2(1)=0.51, Pr>Chi^2=0.4764
F- test for individual effect	F(1,54)=35.733, p-value=1.851e-07

From Table 6 the Hauseman test, showed that for this analysis, the random effect model gives better estimates as the p-value>0.05. Breusch-Godfrey/Wooldridge test for serial correlation in panel models showed that there is serial correlation in idiosyncratic errors. The Breusch- Pagan Lagrange multiplier test for random effect showed there is significant panel effect hence OLS would be inappropriate. The Breusch-Pagan/Cook-Weisberg test for heteroskedsticity showed that heteroskedasticity is not a problem (Wooldridge, 2012).

Table 6 presents the model estimations using the random effect estimates chosen based on the Hauseman test results indicated in Table 6.

3.4. Determinants of Technical Efficiency

Table-7. Random-effect ML regression estimates.

Variables	Coefficient	Std. error	Z-value	Pr(>|Z|)
BOR	-0.1113	0.1882	-0.59	0.555
ALOS	0.0198*	0.0040	4.99	0.000
CPOP	-1.26e-07	6.96e-08	-1.80	0.071
TEASTAT	-0.0389	0.0482	-0.81	0.419
LSIZE	0.0885	0.1149	0.77	0.441
Cons	-0.0229	0.3045	-0.08	0.940
Sigma_u	0.0617	0.0151		
Sigma_e	0.0620	0.0060		
Rho	0.4977	0.1379		
Log-likelihood =82.8112				
LR Chi^2(5) = 32.06 p>Chi^2=0.000				

Note: LR Test of Sigma_u=0 Chi^2(01) =18.15, p>Chi^2=0.000
*significant at 0.05 level

The results presented in Table 7 show that there is significant negative correlation between efficiency and average length of stay (ALOS). The results further shows that 49.77 percent of the variance is due to difference across panels (rho = 0.4977).

4. LIMITATIONS

The study is however limited by the fact that DEA can only classify a group of hospitals as efficient or inefficient relative to an estimated frontier. It does not tell us the ranking of these efficient hospitals among themselves. This frontier depends on the sampled hospitals, changing the composition of the hospitals in the sample may change the efficiency scores. Data availability and accuracy is an issue in the continent and Kenya is not an exception. Thus there was aggregation of data to define certain variables. This may yield results that may not be accurate and reduce their policy relevance.

5. CONCLUSION

Therefore, efficiency is negatively related with ALOS. However, the length of stay in hospital is affected by the ability of the patient to clear the required hospitalization charges. There are cases where patients are detained for failure to clear the bills. Conversely there are cases where relatives pressurize for early discharge for fear of high bills especially in non-life-threatening emergencies. The finding in this study of the negative relationship implies that these hospitals should explore ways of reducing length of hospital stay such as, managing the non-critical cases at home and making financial arrangements for patients to clear bills in instalments once discharged. The home care option would prove effective as patients are cared for in familiar environment. This could be done by engaging more community nurses for regular follow up.

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