UNIVERSITY OF CAPE COAST

COMPARATIVE STUDY OF TECHNICAL EFFICIENCY OF PRIVATE AND PUBLIC CLINICS AND HOSPITALS IN THE CENTRAL REGION OF GHANA

HILDA SERWAA OBENG

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BY

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Thesis Submitted to the Department of Economics, Faculty of Social Sciences, College of Humanities and Legal Studies, University of Cape Coast, in partial fulfilment of the requirements for award of Master of Philosophy degree in Economics

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this University or elsewhere.

Candidate's Signature: --------------------------------- Date: -----------------------

Name: Hilda Serwaa Obeng

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature: ………………………..Date: ………………

Name: Dr. Emmanuel Ekow Asmah

Co-Supervisor's Signature: ………………………….. Date: ……………….

Name: Dr. Isaac Dasmani

ABSTRACT

In Ghana healthcare institutions are not anticipated to be efficient but due to the rising demands on hospital reimbursement levels, focus on efficient operations is becoming more vital. This study compared technical efficiency levels of private and public clinics and hospitals in Central Region. A sample of 34 private and public hospitals and clinics in the Central Region of Ghana was used for the study. The main estimation technique employed was the Data Envelopment Analysis, with four variable inputs and outputs. Furthermore, regression analysis was also used to identify the main determinants of technical efficiency.

The analysis of the data indicates that private clinics have been more technically efficient than their public counterparts. Moreover, the public hospitals were found to be more technically efficient than the private ones. It was also noted that, even though excess input and output variables (slack) were identified for both classes of health facilities, the public clinics and hospitals had greater unutilized resources. The study proved that ownership, experience of administrators and access to clinic or hospital were the main determinants, which also affected the level of technical efficiency. The study recommends that managers and policy makers should identify the areas of inefficiencies in both inputs and outputs for effective reallocation of resources to increase the level of technical efficiency.

ACKNOWLEDGEMENTS

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DEDICATION

To Rev. Prof. Emmanuel Addo Obeng and my beloved husband, Mr. Godfred Arhin.

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KEY WORDS

AE	Allocative Efficiency
CHO	Community Health Officers
CHPS	Community Health Planning and Services
COLS	Corrected Ordinary Least Squares
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DEAP	Data Envelopment Analysis Programme
DMU	Decision Making Unit
EMR	Electronic Medical Record
FTE	Full-Time-Equivalent
GHS	Ghana Health Service
HMO	Health Maintenance Organization
HSMTD	Health Sector Medium Term Development Plan
MDG	Millennium Development Goals
MoH	Ministry of Health
MTHS	Medium-Term Health Strategy
OLS	Ordinary Least Square
SDG	Sustainable Development Goal
SFA	Stochastic Frontiers Analysis
TE	Technical Efficiency
TFP	Total Factor Productivity
VRS	Variable Return to Scale

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CHAPTER ONE

INTRODUCTION

Background of the Study

Ghana is performing relatively better than its neighbours within the West African sub-region on most health indicators (World Bank, 2014). However, these achievements are threatened by limited health resources which confront the country in meeting its health targets such as health-related millennium development goals (MDGs). It is often argued that healthcare institutions are not anticipated to be efficient (Jacobs, 2001), but due to the rising demands on hospital reimbursement levels, focus on efficient operations is becoming more vital. Efficiency measurement in healthcare systems represents a first step towards the evaluation of individual performance of production units, which includes hospitals and health centres. Efficiency is the act of achieving good result with little waste of effort. It is the act of harnessing material and human resources and coordinating these resources to achieve better management goal (Oyewo, 2011).

In Ghana, Ministry of Health (MoH) has the overall responsibility of healthcare delivery in the country. Its goal is to "ensure a healthy and productive population that reproduces itself safely by ensuring that people live long, healthy and productive lives, and reproduce without an increased risk of injury or death; reducing the excessive risk and burden of morbidity, mortality and disability" (MoH, 2014).

The term efficiency is broadly used in economics and refers to the best utilization of resources in production. Typical example of efficiency is technical efficiency, which refers to the effective use of resources in producing outputs. In the Farrell (1957) framework, a hospital is judged to be technically efficient if it is operating on the best practice production frontier in its hospital industry.

Efficiency refers to the success of the hospital in using its resources to produce output – the degree to which the observed use of resources to produce output of a given quality matches the optimal use of resources to produce outputs of a given quality. This can be assessed in terms of technical efficiency or allocative efficiency. The latter type measures whether for any level of production; inputs are used in the proportion that minimizes the cost of production, given input prices. Technical efficiency is concerned with the conversion of physical inputs such as labour services or raw materials into outputs.

The measurement of healthcare efficiency is a difficult exercise for various reasons including the complex nature of the productive process and difficulty in measuring the ideal output of the sector. Within the context of healthcare services, technical efficiency may refer to the physical relationship between the resources allocated (capital, labour and equipment) and certain health outcomes. These health outcomes may either be defined in terms of intermediate outputs (number of patients treated, patient- days, waiting time, etc.) or final health outcomes (lower mortality rates, longer life expectancy, etc.).

Efficiency signifies a level of performance that describes a process that uses the lowest amount of inputs to produce or create the greatest amount of outputs without or less waste. However, Jacob (2001) argued that the healthcare institution is not expected to be efficient because they do not adhere to neoclassical firm optimization. Meanwhile efficient utilization of health resource is a critical requirement for attaining health systems goals particularly in developing countries. It should be noted, however, that many developing countries are below national and international health goals not because of scarcity of resources but because the available resource are not efficiently utilized. According Jehu-Appiah, Sekidde, Adjuik, Akazili, Almeida, Nyonator, Baltussen, Asbu & Kirigia, (2014), there had been marked variations in the regional performance as there are still pockets of low productivity as wastage in the clinics and hospitals.

In the recent years, some effort have been made at developing systems for assessing performance and generating information to assist in the distribution of resource in the health sector. However, most of the measurement has focused on the implementation of services and the intermediate steps that determine how inputs are transformed into output. Several studies have been made on the efficiency of resource in the healthcare industries but in Ghana, few have been identified. Out of that only one centred on ownership of the healthcare institution and technical efficiency while the others focused on one-side, for instance, Osei et al. (2005).

In Ghana, formal health service delivery is executed by teaching hospitals, regional hospitals, psychiatric hospitals, district hospitals, health centres and polyclinics. Primary healthcare services are as well provided by health centres, clinics, Community-based Health Planning and Services (CHPS) compounds and maternity homes. The health sector in most countries, including Ghana is predominantly a public service and therefore influenced by public reforms. Achievements and improvements in health sector are crucially dependent on the performance of staff at all levels which, in turn, is intimately related to their general employment and working conditions. Reforms are changes in systems and methods of work geared towards improving the quality of service rendered to the population and to do so at the best cost effective rates within the context of the society in which the reforms are being carried out.

It is therefore important to measure how health facilities participate in achieving these objectives of the Ministry of Health. One of the popular methods in measuring the efficiency levels of health facilities is the use of Data Envelopment Analysis approach.

Data Envelopment Analysis (DEA) is a widely used technique for the efficiency measurement of hospitals. It has been extensively used in America, Western Europe, and Asia to shed light on the efficiency on various aspects of national health systems. In relation to Africa, the DEA application in the health sector has been quite limited. Some of the African countries in which DEA has been applied include South Africa, Kenya, Zambia and Ghana. Prior research using DEA identified almost half (47%) of a sample of public district hospitals to be inefficient in Ghana (Osei, Almeida, George, Kirigai, Mensah, & Kainyu, 2005). According to Hollingsworth, Rogers and Boyer (1999), DEA is very popular in evaluating hospitals efficiency because it is applicable to the multiple input-output that is essential for the nature of healthcare system.

Statement of the Problem

In recent years, some efforts have been made at developing systems for assessing performance and generating information to assist in the distribution of resources in the health sector. However, most of these measurements have focused on the implementation of services and the intermediate steps that determine how inputs are transformed into outputs. Innovative ways of measuring efficiency, particularly involving the use of simple relational measures, need to be employed gradually to understand some of the disparities in performance as well as providing some guide in the reallocation of resources in a bid to close the inequity gap. One of the pillars of the health sector reforms has been the improvement of efficiency in service delivery.

The Government of Ghana has been implementing various health sector reforms in an effort to improve efficiency in healthcare which include the development of management systems to support service delivery, the implementation of a human resource strategy, which will improve the distribution of health staff across the country, and the adoption of resource distribution criteria that will ensure equity in the allocation of resources. Some of these reforms include user fees in public health facilities, decentralization, and sector-wide approaches to donor coordination, the decentralization of health systems seems not to have translated into improved efficiency and productivity so, in practice, much remains to be done (Jehu-Appiah, et al 2014). Marked variations exist in regional performance and there are still pockets of low productivity and wastage (Jehu-Appiah et al., 2014). Also, few studies exist which estimate that private clinics and hospitals are more efficient than their public counterparts. This paper measures and compares the efficiency level of private and public clinics and hospitals with 2016 input and output factors with much reference to the Central Region of Ghana.

Objectives of the Study

The general objective of this study was to compare the technical efficiency of private and public clinics and hospitals in the Central Region of Ghana. The specific objectives of the study include the following:

(i) Compare the technical efficiency level of private and public clinics and hospitals.

(ii) To determine the level of excess inputs and outputs used in private and public clinics and hospitals.

(iii) Identify the determinants of technical efficiency of private and public clinics and hospitals.

Research Questions

In the context of the objectives, the study seeks to answer the following research questions.

(i) Which private and public clinic and hospital in the Central Region efficiently uses its inputs in production?

(ii) What are the excess inputs private and public clinics and hospitals use in their production?

(iii) What are the determinants of efficiency of inputs used in private and public clinics and hospitals?

Significance of the Study

This study will be of great importance to facilitators of the various hospital, the health directorates of Central Region, the Ministry of Health and the government at large. The findings of the study will go a long way to create awareness among the clinics and hospitals in the form of benchmarking. Clinics and hospitals will find out their loopholes and work harder to improve their performance.

Scope and Delimitation of the Study

The study is quantitative in nature and focused on the level of technical efficiency of public and private clinics and hospitals in the Central Region of Ghana. The research sample is composed of fourteen (14) private and twenty (20) public clinics and hospitals within the region. The study is delimited to four input and output variables respectively to reflect the capacity and scope of sampled facilities. Questionnaire was employed to get quantitative data to measure the level of efficiency of private and public clinics and hospitals in the study area. The DEA approach is applied to the data since this approach allows the measurement of relative efficiency when decision-making units (in this case public and private clinics and hospitals) have multiple inputs and multiple outputs.

In this research, the selection of the health facilities was delimited to clinics and hospitals which were recognized by the Central Regional Health Directorate of the Ghana Health Service. According to Ghana Health Service (2015), the study area has about 52% of its health facilities being CHPS compounds. In this case, the researcher is aware of the greater percentage of primary health facilities involved in the provision of basic and first aid care in the region.

Organization of the Study

This study is organised into five chapters. Chapter one presents the introduction to the topic. It will also entail the background, statement of the problem, objectives and significance of the study. Chapter two mainly dwells on existing literature on the topic. Chapter three is on the methodology, chapter four presents results and discussion and finally chapter five is on conclusion and recommendations.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

Introduction

The literature review focuses on the various forms of efficiency but puts more emphasis on the different approaches to measure technical efficiency. It as well discusses some studies that have been done on technical efficiency of health facilities in Ghana and other related studies in other parts of the world.

The health sector in Ghana is both public and private. The public sector is run by the Ghana Health Service (GHS) and Teaching Hospitals. The private sector is made up of faith-based and private-for-profit health institutions. The public sector is a three-tier health delivery system of primary, secondary and tertiary levels. The primary level is the district and sub-district levels up to the community level. In some sub-districts are Community Health Planning & Services (CHPS) zones where Community Health Officers (CHOs) work with community volunteers to increase access to healthcare. A typical district with a population of 100,000 has one hospital, 5 health centres and 10-15 CHPS zones. The regional hospitals receive referrals from districts and provide outreach support to the districts.

According to Osei et al., 2005, Ghana's health services are organised at the following levels:

1. Community: Delivered through outreach programmes, resident or itinerant herbalists, traditional birth attendants and/or retail drug peddlers.

2. Sub-district: A health centre services in a geographical area with 15,000 to 30,000 populations. It provides basic curative care, disease prevention services and maternity services (primary healthcare). A health centre constitutes an essential component of the close-to-client health services.
3. District: A district hospital provides support to sub-districts in disease prevention and control, health promotion and public health education; referral outpatient and inpatient care, training and supervision of health centres; maternity services, especially the management of complications and emergencies and surgical contraception.
4. Regional: A regional hospital provides specialised clinical and diagnostic care; management of high-risk pregnancies and complications of pregnancy; technical and logistical back up for epidemiological surveillance; and research and training.
5. Tertiary: At the apex of the referral system, there are two government-owned teaching hospitals that offer specialised services, undertake research, and provide undergraduate and postgraduate training in health and allied areas.
6. National (i.e. Ministry of Health headquarters): The national level is responsible for the development of national health policy and for providing strategic directions for service delivery as well as coordination and monitoring.

The Ghana's Ministry of Health, following the thrust of Vision 2020, developed its current policy and strategy guidelines in 1995 in the Medium-Term Health Strategy (MTHS) document. They were based on five main objectives which are: improving access to health services; improving quality of care; improving efficiency; fostering partnership between private and public health service-providers; and improving financing of health services. The underlying objective of the health related programmes adopted in Ghana is to improve efficiency in health service delivery. For instance, one of the main priority health sector-related interventions in the Ghana Poverty Reduction Strategy 2002-2004 highlights "enhancing efficiency in health service delivery". It therefore means that, efficiency is one of the important concerns in major national programmes adopted by the nation.

Many have argued that since healthcare institutions do not adhere to neo-classical firm optimization, they are not generally expected to be efficient (Jacobs, 2001). However, there is a great and growing interest in examining efficiency in hospitals and health institutions due to the numerous amounts of resources that are invested in these institutions.

In an effort to improve the efficiency of health service delivery in Ghana, the Ministry of Health (MoH) set the following policy objectives within the Sector Medium Term Development Plan (HSMTDP) 2014-2017 as the following to:

1. Bridge equity gaps in access to healthcare and nutrition services.
2. Ensure sustainable financing arrangements that protect the poor.
3. Strengthen governance and improve the efficiency and effectiveness of the health system.
4. Improve quality of health services delivery including mental health services.

5. Enhance national capacity for the attainment of the health related MDGs and the gains.
6. Intensify prevention and control of communicable and non-communicable diseases.

The above reviewed strategies by the Ministry of Health seek to enhance the efficiency of health delivery in Ghana.

Measures of Efficiency

According to O'Neill, Rauner, Heidenberger, & Kraus (2008), efficiency measurement represents a first step towards the evaluation of a coordinated healthcare system, and constitutes one of the basic means of audit for the rational distribution of human and economic resources.

Economists have developed three main measures of efficiency: technical, allocative and productive.

Technical Efficiency

Farrell (1957) defined technical efficiency (TE) as the firm's ability to produce maximum output given a set of inputs and technology. He further conceptualized allocative efficiency (AE) as the measure of the firm's success in choosing the optimal input proportions. In the literature there are two main definitions of technical efficiency.

(a) According to Koopmans (1951) " a producer is technically efficient if an increase in an output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output".

(b) Alternatively, Debreu (1951) and Farrell (1957) defined the following measure of technical efficiency known as the Debreu-Farrell measure: "one minus the maximum equi-proportionate reduction in all inputs that still allows the production of given outputs. A value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency".

Technical efficiency can either be output or input-oriented. An output-oriented technical efficiency occurs when the maximum amount of an output is produced for a given set of inputs while an input-oriented technical efficiency occurs when the minimum amount of inputs are required to produce a given output level (Farrell, 1957).

Farrell (1957) further described technical efficiency as the ratio of the firm's observed output and the maximum obtainable output on the frontier given observed factor utilization. Figure 1 illustrates Farrell's arguments.

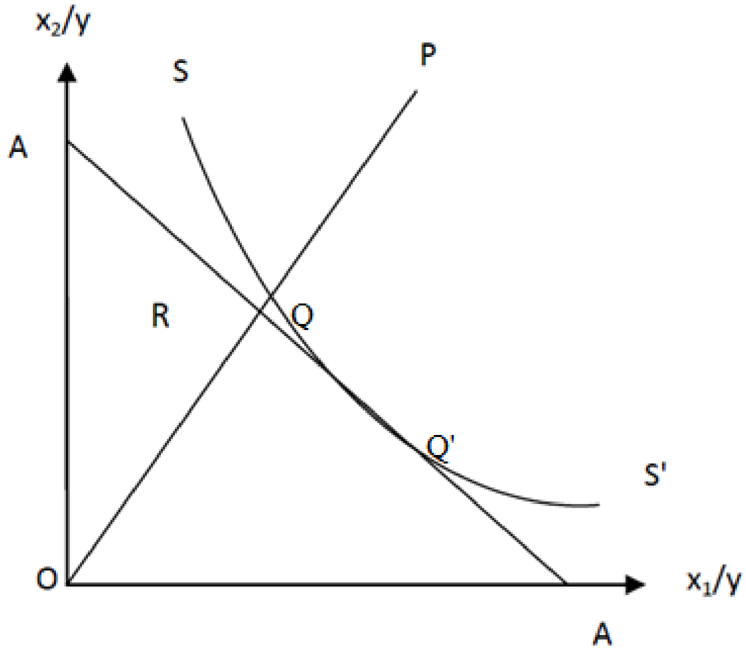

Figure 1: Efficiency measures

Source: Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120.

As per the above figure, x_1 and x_2 are two inputs used to produce a single output y. The production frontier is modelled as $y = f(x_1, x_2)$. We also assume that constant returns to scale is $1=f(x_1/y, x_2/y)$. That is, as inputs increases, the relationship between the inputs and outputs does not change. The isoquant SS' shows various combinations of two inputs that the firm employs to produce a unit of output. The ratio OQ/OP define the level of technical efficiency for a firm using inputs (x_1*, x_2*) to produce a unit of output, y*. That is, point Q indicates an efficient firm using inputs (x_1, x_2) in the same ratio as point P. Therefore, the ratio OQ/OP measures the proportion of (x_1, x_2) necessary to produce y*. It follows that the ratio OQ/OP measures the technical efficiency of the production unit of a firm operating at P. Therefore, 1 - OQ/OP measures the proportion by which (x_1*, x_2*) could be reduced without reducing output. That is, it measures the possible reduction in the cost of producing y*. Point Q lies on the efficient isoquant. If the input price ratio that is represented by the slope of the isocost line is known, and then we can calculate the allocative efficiency. This is referred as Price Efficiency by Farrell. A ratio OR/OQ indicates the production unit's ability to use inputs in optimal proportions, given the respective prices at point P. Therefore 1- OR/OP is the allocative inefficient point. The distance RQ represents the reduction in production costs that would occur if production were to occur at the allocatively and technically efficient point Q' rather than Q.

Therefore, if the production unit was perfectly efficient (both technically and allocatively), then the total economic or productive efficiency would be defined by the ratio OR/OP. The total inefficiency is therefore 1-OR/OP. We can interpret the distance RP in terms of the cost reduction achieved by moving from the observed point P to the cost minimizing point Q'.

Allocative Efficiency

Allocative efficiency reflects the ability of an organization to use inputs in optimal proportions, given their respective prices and the production technology. In other words, allocative efficiency is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs.

Productive Efficiency

According to Worthington (2004), when allocative efficiency and technical efficiency are taken together it determines the degree of productive efficiency. This is as well identified as total economic efficiency. Alternatively, to the extent that either allocative or technical inefficiency is present, then the organization will be operating at less than total economic efficiency (Staat 2006).

The Concept of Hospital Efficiency

In the Farrell (1957) framework, a health unit is judged to be technically efficient if it is operating on the best practice production frontier in its hospital industry. In the original Farrell framework, the entire observations on given sample is assumed to have access to same technology (Grosskopf & Valdmanis, 1987)

Magnussen (1996) stated that measuring technical efficiency allows us to compare hospitals in terms of their real use of inputs and outputs rather than costs or profits. A hospital is said to be technically efficient if an increase in an output requires a decrease in at least one other output, or an increase in at least one input. Alternatively, a reduction in any input must require an increase in at least one other input or a decrease in at least one output. On the other hand, allocative efficiency occurs when inputs or outputs are put to their best possible uses in the economy so that no further gains in output or welfare are possible.

To measure hospital's efficiency, the hospital's output(s) must be identified. There are many potential measurements for a hospital's outputs such as number of cases treated, number of procedures performed, and number of patient days, bed turnover, and bed occupancy, among others. Which output or combination of outputs to use depends on the objectives of the hospital and on the level of measurement activities (e.g. departmental and institutional level).

Approaches for Measuring Technical Efficiencies

Several approaches have been adopted in estimating technical efficiencies. The most commonly used approaches include: the Malmquist index, the Data Envelopment Analysis (DEA) and the stochastic frontiers. The DEA and SFA (Stochastic Frontier Analysis) employ quite distinct methodologies for frontier estimation and efficiency measurement, each with associated strengths and weaknesses, such that a trade-off exists in selecting the correct approach (Mortimer, 2002). Banker, Gadh and Gorr (1993) show that DEA is favoured when measurement error is an unlikely threat and where the assumptions of neoclassical production theory are questionable. SFA, on the hand, deals with severe measurement error and where simple functional forms provide a close match to the properties of the underlying production technology.

Data Envelopment Analysis (DEA)

DEA, is a non-parametric (i.e., non-statistical) or mathematical programming approach for considering optimum solutions relative to individual units (e.g., firms) rather than assuming, as in optimized regression, that a solution applies to each decision-making unit.

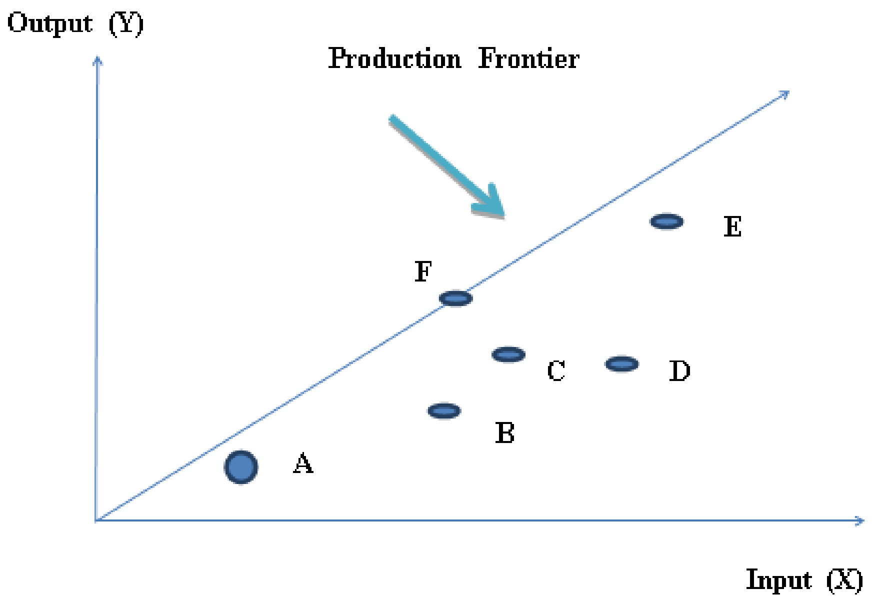

Figure 2: The CCR production frontier

Source: Charnes, W., et al. (2006). Introduction to data envelopment analysis and its uses: With DEA-solver software and references. New York: Springer, 81.

This model is named after its developer Charnes, Cooper and Rhodes (CCR). It is the first and fundamental DEA model, built on the notion of efficiency as defined in the classical engineering ratio. The model calculates an overall efficiency for the unit in which both its pure technical efficiency and scale efficiency are aggregated into a single value. The obtained efficiency is never absolute as it is always measured relative to the field. In Figure 2, under the simplistic assumption that there is only one input and one output, for the Charnes, Cooper & Rhodes (CCR) model, due to the CRS assumption, the DMU at point F lying on the efficient (production) frontier is the only CCR-efficient DMU because its efficiency score $a\eta$ equals 1. The remaining DMUs (i.e. $DMU_{A,\ B,\ C,\ D\ \text{and}\ E)}$ are inefficient due to their efficiency score being smaller than 1($a\eta$ <1). Additionally, the essence of the CCR DEA model is that, there is no DMU lying in the area under the frontier (straight line), which could be more efficient than the $DMU_{F.}$ Similarly, no combination between the inefficient DMUs could generate higher efficiency score than the DMU_F. The "primal" and the "dual" CCR models would lead to the same efficiency scores in both the "input-oriented" and the "output-oriented" approaches due to Constant Returns to Scale.

There are two primary orientations of the DEA approach to assess technical and economic efficiency: input- and output-oriented. The input-based measure considers how inputs may be reduced relative to a desired output level. The output-based measure indicates how output could be expanded given the input levels. This approach has been adopted by Fulginiti & Perrin (1997; 1998), Arnade (1998), Coelli et al. (1998). A recognized limitation of using DEA to assess technical efficiency is that, recommendations for decreasing input usage or expanding output levels are in terms of scalar valued ratios which are held constant (i.e., recommendations are in terms of fixed proportions).

Malmquist Productivity Index

The Malmquist productivity index introduced by Caves, Christensen & Diewert (1982) is a binary comparison of two entities; the input and output distance functions. Färe, Grosskopf, Norris & Zhang (1994) extended the index to allow for productivity comparison between one sector and another and for decomposition of total factor productivity into change in technical efficiency and technological change. The approach measures productivity change by comparing observed change in output with the imputed change in output that would have been possible from the observed input changes. The imputation is based on the production possibility set for either the current or the subsequent period. During the computations, it makes use of DEA to generate the ratio of two distance functions (input and output distance functions) and their geometric mean (Färe et al., 1994). Several empirical studies have adopted this approach (Grifell-Tatjé & Lovell 1995; Fulginiti & Perrin 1997; Coelli & Rao 2003)

Stochastic Frontier

The stochastic frontier approach specifies the relationship between output and input levels using two error terms. One error term is the traditional normal error term in which the mean is zero and the variance is constant. The other error term represents technical inefficiency and may be expressed as a half-normal, truncated normal, exponential, or two-parameter gamma distribution. Technical efficiency is subsequently estimated via maximum likelihood of the production function subject to the two error terms (Aigner, et al., 1977; Meeusen & Van den Broeck, 1977). Empirical studies that use the stochastic frontier production function follow either the two-step approach that first estimates the stochastic frontier production function to determine the technical efficiency indicators and thereafter, these indicators are regressed on explanatory variables, which usually represent the decision making units' specific characteristics, using the ordinary least square (OLS) method. Like many other approaches, the estimation of this approach is not free of limitation. Its major drawback is the assumption that the inefficiency effects are independent and identically distributed. To overcome this, Reifschneider and Stevenson (1991) developed a model in which inefficiency effects are defined as an explicit function of certain factors specific to the decision making units, and all the parameters are estimated in one step using the maximum likelihood procedure, and hence the one-step approach.

DEA and SFA Model

The overall efficiency of any clinic has two major components, that is, technical and allocative efficiency. A clinic is considered to be technically efficient if it is able to produce maximum output from a given set of inputs. A clinic is allocatively efficient if it is able to use the inputs in optimal proportions, given their respective costs. As the relevant data on costs of inputs were not available in this study, the allocative efficiency measures were not employed. DEA with 'input orientation' consider the limited control of private and public clinics in the region over their outputs. It also addresses the question: by how much can input quantities be proportionally saved without changing the output quantities produced?

DEA can be defined as the fraction of weighted sum of outputs to weighted sum of inputs. Given *n* outputs and *m* inputs, efficiency (h_0) for hospital 0 is defined as follows:

$$maximise: \quad h_o = \frac{\sum_{r=1}^{n} u_r \times y_{r0}}{\sum_{i=1}^{m} V_i \times x_{i0}}$$

Subject to (1)

$$\frac{\sum_{r=1}^{n} u_r \times y_{r0}}{\sum_{i=1}^{m} V_i \times x_{i0}} \leq 1 \qquad j = 1, \ldots, n$$

y_{r0} = quantity of output *r* for clinic 0

u_r = weigh attached to output *r*, $u_r > 0$, $r=1, \ldots\ldots, p$

x_{i0} = quantity of input *i* for clinic 0

v_i = weight attached to input *i*, $vi>0$, $i = 1,\ldots\ldots\ldots\ldots, m$

The weights are specific to each unit so that $0 \leq w \leq 1$ and a value of unity imply complete technical efficiency. DEA computes all possible sets of weights which satisfy all constraints. Hospital unit that is the highest efficiency with the given data of inputs and outputs for the specific period of time in our case it is year 2015.

Assume each of I decision making unit consumes m different inputs, to produce outputs Let $x_{ij} \geq 0$ denote the inputs i consumed and $y_{rj} \geq 0$ denote the output r produced by decision making unit j. Assume $x_{ij} > 0$ and $y_{rj} > 0$ for some i and r for all j. Then the problem of DEA can be stated as:

$$\max h_0(U,V) = \sum_r u_r y_{r0} / \sum_i V_i X_{i0} \qquad (2)$$

subject to:

$$\sum_r u_r y_{rj} / \sum_i V_i X_{ij} \leq 1 \;\; for\; j = 1, \ldots, n \; and \; u_r, V_i \geq 0 \; for\; all\; i, r \qquad (3)$$

Equation 1 is normalization constraint for each decision making unit. However, this problem will have infinite number of solutions. Since for different levels of virtual input, we will have different levels of virtual output. Thus, by imposing

$$\sum_{i=1}^{m} V_i X_{i0} = 1$$

Charnes et al. (1978) take a representative solution. The problem becomes maximizing the virtual output given a predetermined level of virtual input. Then the maximization problem will be:

$$\max z = \sum_r \mu_r y_{r0} \qquad (4)$$

subject to:

$$\sum_r \mu_r y_{rj} - \sum_i V_i X_{ij} \leq 1 \quad for\; j = 1, \ldots, n \qquad (5)$$

$$\sum_{i=1}^{m} V_i X_{i0} = 1 \;\; and \;\; \mu_r, V_r \geq 0 \;\; for\; all\; i, r \qquad (6)$$

The solution to the above problem will be vectors Y and X, which will consist of μ_r s and v_i s and finally z will be the efficiency score.

The calculated z scores were excepted as a dependent variable in logistic regression model. Dependent variable is generally integrated to the analysis in binary form in the logistic regression model which is widely used. In an alternative use of the logistic regression model, the dependent variable is continuous, but this alternative offers limited range (Manning, 1996).

The logistic regression model offers various virtues. Firstly it is easily transformed into a simple linear regression and secondly it yields predicted values within the natural boundaries of dependent variable. According to classical assumptions, ordinary least squares estimation of the logit model is also free of the heteroscedasticity problem caused by the use of the logistic regression with bounded continuous data (Maddala, 1983).

S, which is between zero and unity and which is a function of a vector of dependent variables and X and some error term, ε, symmetrically distributed around zero are bounded continuous variables. When we apply the functional form of the logistic distribution on these variables, we obtain the following finding:

$$S_i = \frac{1}{1+e^{-X_i\beta+\varepsilon_i}} \qquad (6)$$

Then we see that standard transformation then produces the simple linear regression equation:

$$\log\left(\frac{S_i}{1-S_i}\right) = X_i\beta + \varepsilon_i \qquad (7)$$

Empirical Literature Review

Gok and Sezen (2011) in their application of DEA to investigate the efficiencies revealed some findings with respect to the hospitals in Turkey. Per the output and input variables considered between 2001 and 2006 it was identified that the average efficiencies of state hospitals remarkably increased while the average efficiencies of private hospitals decreased in 2003. Malmquist Productivity Index also confirmed that, the technical efficiencies of state hospitals markedly increased for the period of 2003-2004.

Sulku (2012) investigated the impact of the health sector reforms on the efficiency of public hospitals in Turkey. The DEA and the Malmquist index were employed to comparatively examine before and after the reforms years. The analyses compared the performances of public provincial markets. The inputs included number of beds, number of primary care physician, and number of specialists and how they are used to produce outputs of inpatient discharges, outpatient visits and surgical operations. The investigation revealed that the Health Transformation Programme was generally successful in boosting productivity due to advancements in technology and technical efficiency. Technical efficiency component has improved during the 2001-2006 period. However, the average increase of pure technical efficiencies was very low compared to that of scale efficiencies. It was as well noted that the socio-economically most disadvantaged provinces, productivity gains have not been achieved because of the deterioration in the technical efficiency, even though there was an improvement in the technological progress. There was as well rapid rise from a stagnant and inefficient system into an active system in the short run.

In Vietnam, Nguyen and Giang (2007) also investigated the effects of three determinants of technical efficiency, namely size, location, and capital or labour intensity. The DEA and tobit models were applied in the research using data collected from 17 hospitals and 27 medical centres in Vietnam. Their findings showed that location did not influence efficiency levels and both groups of hospitals and medical centres were labour intensive. However, the size of the healthcare institutions had a positive correlation on the efficiency levels. Notwithstanding the technical shortcomings of the study, this observation led the researchers to suggest that hospitals were much more technically efficient than medical centres.

Grosskopf and Valdmanis (1987) in their empirical studies investigated the factor of hospital ownership on the level of technical efficiency of hospitals in California. The researchers compared private and public 'not-for-profit' hospitals and found that public hospitals were more technically efficient as a result of better resource management and a better 'best practice' production frontier.

However, a further research conducted by Valdmanis (1990) found that private hospitals were able to provide a broader range of medical services compared to the public ones. The researcher applied the DEA method to a group of hospitals and found that government-owned hospitals were more efficient and this might be due to the fact that an imperfect adjustment is made for the quality of output patient day rather than admission are generally used to measure output. The other surprising result is that for profit hospitals tend to be disproportionately represented among highly inefficient hospitals (Ozcan et al., 1992) and are inefficient compared to not-for-profit hospitals when output is measure by discharging.

A similar study by Ozcan and Bannick (1994) considered the type of hospital ownership as one of the major factors behind the large variations of technical efficiency in hospitals. The study compared hospitals owned by the US Department of Defense (DoD) and the civilian hospitals. The authors estimated the efficiency scores for hospitals owned by DoD (Army, Navy and Air-Force) and a large number of civilian hospitals and was found that the DoD hospitals were much more technically-efficient compared to the civilian ones. However, the researchers concluded that DoD hospitals had some idiosyncratic aspects which should have taken into account, such as the different medical objectives, the different employment conditions of medical staff, different organisational patterns and, of course, different groups of patients served.

In another study in US, Mobley and Magnussen (1998) explored the consequences of having different type of hospital ownership on efficiency level. The researchers assessed efficiency levels of public and private hospitals in the United States and Norway. The result of the study revealed that the private US hospitals were at least equally-efficient as the publicly-funded Norwegian hospitals. The longer-term efficiency was found to be due to better utilization of bed capacity in Norwegian hospitals, a significant source of inefficiency in both the US public and private hospitals.

Ozcan & Luke (1993) used the DEA technique to conduct a national study of the efficiency of hospitals in urban markets. Four variables were analyzed in this study: hospital size, membership in multihospital system, ownership and payer mix. Ownership and Medicare were consistently related to hospital efficiency. The Medicare was related negatively to technical efficiency. Government hospitals were more efficient and for profit hospitals less efficient than other types of hospitals. Other variables like hospitals size, and membership in a multihospital system were related positively to efficiency.

A further study by Ozcan, McCue and Okasha, (1996) considered the efficiency levels of psychiatric hospitals as a separate group and compared those with hospitals of acute care for the time period 1986-1990. The study included ‘not-for-profit’ and ‘for-profit’ hospitals. According to the authors, the analysis of the data over the five years revealed that the psychiatric hospitals appeared to be less efficient than acute care hospitals. However, no statistically significant differences were determined between the ‘not-for-profit’ and ‘for-profit’ groups of hospitals.

Bates (2006) used data envelopment analysis and multiple regression analysis to examine empirically the impact of various market-structure elements on the technical efficiency of the hospital services industry in various metropolitan areas of the United States. Market-structure elements include the degree of rivalry among hospitals, extent of Health Maintenance Organization (HMO) activity, and health insurer concentration. The DEA results showed the hospital services industry experienced 11% inefficiency in 1999. Moreover, multiple regression analysis indicated the level of technical efficiency varied directly across metropolitan hospital services industries in response to greater HMO activity and private health insurer concentration in the state. The analysis indicated that, the degree of rivalry among hospitals had no marginal effect on technical efficiency at the industry level.

Pelone, Reeves, Ioannides, Emery, Titmarsh, Jackson, Hassenkamp, Greenwood (2015), presents a systematic literature review into the analysis of primary care efficiency through the use of data envelopment analysis. In order to comprehend how results are impacted by methodological frameworks, as well as the information that policy makers receive the researchers reviewed 39 specific DEA applications that are present within primary care. This paper also described a combination of investigations that utilised the qualitative narrative synthesis. Additionally, data are reported from this study through each efficiency analysis in the context of evaluation, specification of model, application of methods in order to test the findings' durability, and the presentation of results.

Overall, it is indicated by the results in relation to the application to primary care that the DEA requires additional developments to enable the complex production of primary care outcomes, although it is still a perpetually developing methodology. However, the improvement of the efficiency of primary care organisations by policy makers and managers is supported by continual evaluations. Nevertheless, enhanced research remains a requirement to address certain areas of ambiguity in this particular field of investigation. For instance, the standardisation of methodologies and the development of outcome research in primary care require improvement and clarification. Likewise, it is conclusive that additional research will have to be structured from beneficial evidence-based rationales and incorporate substantial uncertainty analyses. The researchers have proposed to different academics and scholars that various considerations should be analysed in order to understand the process of decision-making in primary care from the utility of efficiency measurement.

Nayar and Ozcan (2008) studied the performance measures of quality for Virginia hospitals. The findings indicate that technically efficient hospitals showed good performance as far as quality measures were concerned. Some of the technically inefficient hospitals were also performing well with respect to quality. Kazley and Ozcan (2009) examined the relationship between hospital electronic medical record (EMR) use and efficiency among a large number of acute care hospitals. The findings indicate that small hospitals may benefit in the area of efficiency through EMR use, but medium and large hospitals generally do not demonstrate such a difference. Barnum et al. (2011) compared the efficiencies of 87 community hospitals. These results suggest that conventional DEA models are not suitable for estimating the efficiency of hospitals unless there is empirical evidence that the inputs and outputs are substitutable. Sulku (2012) compared the performances of public hospitals serving in provincial markets of Turkey following the introduction of new programs.

Inputs such as the numbers of beds, primary care physicians and specialists were examined for the outputs of 31 inpatient discharges, outpatient visits and surgical operations that were investigated. The findings indicate that average technical efficiency gains took place because of the significantly improved scale efficiencies, as the average pure technical efficiency slightly improved.

Alonso et al. (2013) used the DEA method with bootstrap to analyse and compare efficiency scores in traditionally managed hospitals and those operating with new management formulae. The study indicates that the skills and involvement of the management is a major factor. Mohammadi and Iranban (2015) used DEA to study the hospital efficiency in Iran. Inputs for the study included the costs of materials and service variables, as input indices and the safety standards in the archive, the number of new incoming certificates and patient satisfaction were considered as output indices. Wang et al. (2015) used the DEA method to study the efficiency of 18 hospitals in Shanghai for 2008-2013. The study helped to assess the areas of inefficiency and methods to improve the efficiency.

Hollingsworth et al. (1999) reviewed 91 studies involving DEA modelling for measuring technical efficiency in healthcare. The authors found that most of the studies were focused on measuring hospital efficiency, particularly in the United States. The most important observation was that DEA modelling was found to be more successful and more accurate in measuring overall hospital efficiency, rather than the efficiencies associated with certain departments or groups of medical professionals. For example, it was easier for the DEA linear programmer to calculate the technical efficiency of a hospital as a whole, given certain organisational and managerial restrictions, but it was much more challenging to identify differences in efficiency levels among hospital departments.

Furthermore, the review by Hollingsworth (2003) identified that half of the 188 reviewed studies involved non-parametric approaches to measuring technical efficiency in hospitals, revealing the importance of assessing hospital efficiency. This review showed that there have been significant attempts to introduce more advanced versions of DEA programming in studies measuring hospital efficiency, such as the two-stage DEA approach using the tobit model. In the same review, certain parametric approaches and the SFA found empirical validity, as well. However, the author concluded that DEA remains the predominant method used for measuring technical efficiency in the healthcare sectors. Nonetheless, these comprehensive reviews demonstrated that the availability of systematic data sets might also be a factor explaining why hospitals were found to be more appropriate than other healthcare institutions in terms of applying alternative methods for measuring technical efficiency.

Gakuru (2006) used DEA to estimate technical efficiency in the delivery of healthcare services in the public hospitals of Kenya, and obtained data from 63 hospitals. Inputs used included doctors/pharmacists, clinical officers, nurses, expenditure on buildings and maintenance, and expenditure on drugs. Outputs used were inpatient days and outpatient visits. Logit model was applied to identify factors affecting hospital efficiency. 30 % of the hospitals were found to be efficient. 21 % of the hospitals had a scale efficiency of 100 %.

Mutuku (2008) used DEA to assess technical efficiency of the Nairobi City Council health facilities. He collected data from fifteen out of 48 facilities under the Nairobi health management board for the years 2006 and 2007. The study used two inputs and three outputs. The outputs included attendance in the children's clinic; number of antenatal visits and number of curative patients, while inputs used were number of nurses /clinical officers and number of support staff in the facilities. Productivity change was analysed for two years. The results showed that the health facilities had a mean technical inefficiency of 24.1%.

Kirigia et al. (2001) used DEA to evaluate the Technical efficiency of public clinics in Kwazulu-Natal province of South Africa. The study revealed that out of 155 primary healthcare clinics in Kwazulu-Natal province in South Africa, 70% were technically inefficient. In another related study by Kirigia et al. (2002), it was observed that 26% (14) of the hospitals in Kenya were technically inefficient as against 74% (40) efficient hospitals. Kirigia et al. (2004), in their analysis to measure the technical efficiency of public health centres in Kenya with DEA, found out that 44% of public health centres are inefficient.

Tamiru (2002) examined the technical efficiency of 40 health centres in Ethiopia. He employed DEA model for a one year data set to obtain the efficiency scores and regressed the efficiency scores against health centre operating characteristics using both OLS and Logit models. He used five inputs: Doctors/health officers, nurses, health assistants, other technical staffs, administrative staff and three outputs: Outpatient visits, maternal & child care visits and delivery services. He used DEA results as the dependent variable for logit model, while his independent variables were healthcare operating characteristics, specifically population of the area, patients treated per health worker per day, availability of healthcare unit and location of health facility. He found out that 60% of the health centres were technically and scale inefficient. The regression results showed that location and availability of public hospitals in the area were significantly associated with efficiency levels. The study however did not analyse productivity change.

Zere (2000) estimated technical efficiency and productivity of a sample of 86 hospitals classified as level I, level II and level III in South Africa. The output variables used were outpatient visits and inpatient days while the input variables were total recurrent expenditure and bed-size. The results showed overall technical efficiency of 0.74, 0.68 and 0.70 for the levels I, II and III, respectively. Results from the Tobit model revealed that the ratio of outpatient visits to inpatient days was statistically significant at 95 %

significance level. The study however did not include national referral hospitals in South Africa.

Renner et al. (2005) measured technical and scale efficiency of 37 peripheral health units in Sierra Leone. They used a onetime period sample data and employed DEA. Inputs included: technical staff and subordinate staff while outputs included: ante-natal and post-natal visits, child deliveries, nutritional/child growth monitoring visits, family planning visits, immunized children and pregnant women and total number of health education sessions. They found that 22(59%) were technically inefficient, and 24(65%) were scale inefficient. The main limitation of the study was the sample data. They used a single time period data, which might have led to bias due to extreme observations. The study did not assess productivity change.

Masiye et al. (2002) used DEA to measure technical and allocative efficiencies of twenty hospitals in Zambia. The study estimated two models. The first model used one input and five outputs namely: total expenditure, outpatient visits for children aged less than five years, outpatient visits for children aged over five years, bed days for children aged less than five years, bed days for over five years and number of deliveries. The second model used three inputs consisting of non-labour expenditure, number of doctors and clinical officers, number of other personnel and three outputs namely total outpatient visits, total number of bed days and number of deliveries. Model two included price variables that helped to analyse allocative efficiency. Under the first model, 75% of the hospitals were technically inefficient with a mean score of 0.441. Under the second model, 50% of the hospitals were technically inefficient with a mean score of 0.543. 85% of the hospitals were allocatively and economically inefficient. The study however, did not estimate input reductions or output increases to make the inefficient hospitals efficient.

Owino and Korir (1997) conducted a study which estimated efficiency in public hospitals in Kenya. The researchers used both secondary and primary data. The secondary data were collected from the health information systems at the Ministry of health. The primary data was collected through a survey of 26 hospitals. A non-linear short run variable cost function was estimated, with explanatory variables average wage, outpatient visits, admissions, and beds. Their analysis indicated an average inefficiency level of 30%, increasing returns to variable factor inputs, existence of economies of scale that the public hospitals were operating at higher than minimum average costs, and low responsiveness of recurrent costs to changes in hospitals' capacity and output. The researchers concluded by attributing the inefficiency to shortage of professional staff; poor combination of inputs; irregular or non-functioning theatres and laboratories; transport problems; lack of, or mal-distribution of drugs and medical supplies; and frequent breakdown and or poor servicing of machines and equipment. This study considered panel data, allowed for time varying efficiency, and employed both econometric and DEA models to improve the readability of the estimates of efficiency. All the explanatory variables were statistically significant at 5% level, except the output score. The study did not evaluate productivity change.

Jehu-Appiah et al. (2009) conducted a situational analysis of technical efficiency of district hospitals in Ghana. Some of the findings identified through the application of DEA model to 128 district hospitals were: approximately 76% of district hospitals in Ghana are inefficient; Quasi-government hospitals are the most efficient making them the best performing in terms of technical efficiency, followed by government, mission and private hospitals. The study as well demonstrates that government hospitals in Ghana show higher levels of technical efficiency than their private counterparts.

In another related study, Jehu-Appiah et al. (2014) analysed ownership and technical efficiency of hospitals with evidence from Ghana using DEA. This retrospective study used DEA to estimate the efficiency of 128 hospitals made up of 73 government hospitals, mission hospitals, seven quasi-government hospitals and six private hospitals in Ghana. The lowest-performing hospitals had efficiency scores ranging from 21% to 30%. Quasi-government hospitals had the highest mean efficiency score (83.9%) followed by public hospitals (70.4%), mission hospitals (68.6%) and private hospitals (55.8%).

However, public hospitals also got the lowest mean technical efficiency scores (27.4%), implying they have some of the most inefficient hospitals. Regarding regional performance, Northern Region hospitals had the highest mean efficiency score (83.0%) and Volta Region hospitals had the lowest mean score (43.0%). From their regression, it was found out that while quasi-government ownership is positively associated with hospital technical efficiency; private ownership negatively affects hospital efficiency. Their analysis did not take into consideration the differences that may exist between the categories of nurses and doctors in the various hospitals. In addition, even within the same health workforce category, the quality of labour input may vary depending on individual health worker skills, professional experience and health status.

Osei et al. (2005) also used DEA to measure technical efficiency of public district hospitals and health centres in Ghana. The sampled district hospitals (17) and health centres (17) were analysed with DEA model with 7 and 6 variables respectively. The results of this pilot study revealed that eight (47%) hospitals were technically inefficient, with an average Technical Efficiency (TE) score of 61% and a standard deviation (STD) of 12%. It was further identified that out of the 17 health centres, 3 (18%) were technically inefficient, with a mean TE score of 49% (STD = 27%). Among the limitations noted in this study was the fact that all the hospitals studied were district-level public hospitals, designed and resourced to provide a fairly similar level and mix of care. It is unlikely that there would be any significant variance in the quality of care across these facilities. Another setback to this study was on the sample size used for the analysis. The sample for health centres constituted only 3.7% of the total number of public health centres and hospitals formed about 22% of the public district hospitals, the results cannot be generalized to the entire population of health centres and hospitals in Ghana.

Akazili et al. (2008), sought to estimate the technical and allocative efficiency of health centres in Ghana. The study used DEA method to calculate the technical and allocative efficiency of 113 randomly sampled health centres in Ghana. A logistic regression model was also applied to determine the factors that significantly influence the efficiency of health centres. Their findings showed that 78% of health centres were technically inefficient and so were using resources that they did not actually need. Eight percent were also allocatively inefficient. The overall efficiency as identified by the study, (product of the technical and allocative efficiency), was also calculated and over 90% of the health centres were inefficient. The results of a logistic regression analysis show that newer health centres and those which receive incentives, were more likely to be technically efficient compared to older health centres and those who did not receive incentives.

A study conducted by Dasmani (2012) assessed the determinants of technical efficiency of small-scale batik producers in the Central Region of Ghana. The results indicated that the mean technical efficiency of Ghana's batik production industry was 66.5 percent on the average: ranging from 8.4 to 99.6 percent. The wide variation in the level of efficiency suggests that there was ample opportunity for these enterprises to raise their level of efficiency. The level of education, business experience, and training programs of entrepreneur and accessibility to credit were found to be highly positively significant in affecting the level of efficiency of the batik enterprises. The study suggests that more resources be invested in the training of the entrepreneurs and access to credit should be improved to increase the technical efficiency of batik entrepreneurs in Ghana. It suggests that labour is one of the major variable inputs which determine the efficiency level of a firm hence the need to consider the clinical and non-clinical staff as major variable inputs in this study.

Conclusion

The reviewed literature has drawn the utilization of DEA as a dependable and effective technique for evaluating technical efficiency levels in especially health institutions and other non-health related institutions due to data specification and accessibility. It is noted from the review that most of the studies considered the key inputs and outputs variables for their analysis. Some studies covered multiple years to make effective analysis. However, some of the setbacks identified in the review of these studies included: the small sample size used for analysis; productivity changes not considered as well as estimate of input reductions and output increases to achieve efficiency not being considered. It is also noted that these studies reviewed have largely ignored clinics in the region, a gap that has been filled by this research paper.

CHAPTER THREE

RESEARCH METHODS

Introduction

The chapter presents details of the methodology adopted for the study. It also explains how the relevant data and information are used to address the research objectives and provide an insight on the estimation procedure that was adopted in estimating the level of efficiency of public and private clinic and hospitals in the Central Region, Ghana.

Research Design

The quantitative research design was adopted to analyse the level of efficiency of public and private hospitals and clinics in the study area. The quantitative method was adopted to classify features, count them, and construct statistical models in an attempt to explain what is observed. Also, to seek precise measurement and analysis of target concepts in research study. Most of the tools for measuring healthcare efficiency used econometric or mathematical programming methodologies. Two common approaches identified were: DEA and SFA. DEA is a non-parametric deterministic approach that solves a linear programming problem in order to define efficient behaviour.

The Study Area

The study was conducted in the Central Region of Ghana. Central Region is one of the ten administrative regions in Ghana. It shares borders on the east with the Greater Accra Region, on the north with Ashanti Region and on the north-east with Eastern Region. The Central Region occupies an area of 9,826 square kilometres, which is about 6.6% of the land area of Ghana. It has 20 administrative districts with the historical city of Cape Coast as the capital.

Population

The Central Regions' population of 2,564,978 as projected by the Ghana Statistical Service for the year 2015 is served by a total of 415 health facilities. Out of the total number of health facilities, 219 are Community-based Health Planning and Services (CHPS) compounds, 67 clinics, 27 hospitals, 64 health centres, 15 midwife or maternity homes, 2 polyclinics and 1 psychiatric hospital. The composition of the total clinics and hospitals in the region is close to 23% of the total health facilities. However, as presented by Ghana Health Service (2015) in its annual report "*The Health Sector in Ghana: Facts and Figures, 2015"*, the region has about 52% of its health facilities being CHPS compounds.

The region also has one teaching hospital in Cape Coast which support the School of Medical Science of University of Cape Coast. Furthermore, it has one Trauma and Specialist Hospital in Winneba designated as regional hospital. All these health facilities are serviced by a little over 100 doctors, along with other paramedical and support staff. It is noted that most of the privately owned clinics and hospitals are located in the district capitals and other big towns.

Sampling Procedure

The study employed a primary data from secondary sources from selected clinics and hospitals in the Central Region of Ghana. From initial sample of 97 clinics and hospitals in the region, completed data was available for 34 clinics and hospitals in the variable required for the analysis. The data set for this study was collected for the financial year period of 2016 using a questionnaire adapted from WHO regional office being used by Jehu-Appiah et al. (2014). Out of the 34 questionnaires, fourteen (14) were private and twenty (20) public clinics and hospitals within the region. Four variable output and four variable input were considered for the study due to the nature of the DEA which include multiple input and output. Also, a regression analysis was used to find out the main determinants of technical efficiency of the various clinics and hospitals in the study area.

Data Collection Instruments

In choosing a method to do research you have to consider what is the most appropriate method for investigating a particular research problem or question. The use of questionnaire was employed for the study due to its numerous strengths, which include the following; firstly, administration is comparatively inexpensive and easy even when gathering data from large numbers of people spread over wide geographic area. Also, it reduces chance of evaluator bias because the same questions are asked of all respondents. Some people also feel more comfortable responding to a survey than participating in an interview. Lastly tabulation of closed-ended responses is an easy and straightforward process. Aside these advantages there are some challenges in the use of the questionnaire. These include; Survey respondents may not complete the survey resulting in low response rates. Items may not have the same meaning to all respondents. Size and diversity of sample will be limited by people's ability to read. Also, given lack of contact with respondents, the researcher may not know who really completed the survey and lastly good survey questions are hard to write and they take considerable time to develop.

The questionnaire was designed in three parts. The first part gives the background information of the administrator. The second and the third part give information about the input and output of the clinics and hospitals respectively. This questionnaire was employed to get quantitative data to measure the level of efficiency of private and public clinics and hospitals in the study area. Upon visiting hospitals and clinics in the region, 34 clinics and hospitals were chosen for the study. Out of the total of 64 hospitals and clinics recognised in the region, 34 of them were ready to fill the form and provided all needed information on the questionnaire. The inputs and outputs data were collected for the year 2016.

Fieldwork

The administration of the questionnaire started on 13th March, 2017 after visiting the Central Regional Health Directorate for permission. The first week was used to administer the questionnaire to the selected clinics and hospitals in Cape Coast. The remaining days were used to visit the other clinics and hospital outside Cape Coast but within the Central Region. The entire exercise started from 13th March and ended in the latter part of May,

2017. Due to the nature of the research, the research employed three personnel to assist in the distribution of the questionnaire. Lack of proper documentation in some clinics and hospitals was one of the major challenges. Some administrators were finding it difficult to assist even though an introductory letter was attached. Furthermore, some of the questionnaires were not returned even though several attempts were made to retrieve them. Lastly, mishandling and improper filling of the forms made it difficult to work with.

Data Processing and Analysis

The questionnaire was coded using SPSS and later run using the DEAP version 2.1 to get the efficiency scores. In the second stage, the background data was regressed against the ownership to identify some determinants of efficiency for both private and public clinics and hospital using stata.

Study Variables

In modelling the health service production, the study used four input and four output variables. As observed by Alkazili (2008) that the selection of input and outputs for DEA needs careful attention as it may affect the distribution of technical efficiency. Firstly, the selection of the variables for this study was guided by a review of the literature on the clinic efficiency assessment using DEA. These input and output factors were as well considered because of their relevance to primary healthcare which is the main focus and preoccupation of sampled private and public clinics in the Central Region of Ghana. These factors were also selected because of their relevance in attainment of the health related MDGs in Ghana. Moreover, there were adequate data on these inputs and output factors in the sampled health facilities.

The number of inputs (n = 4) and outputs (n = 4) used for the DEA was also consistent with approaches by previous related studies to avoid extreme trade-off between estimated efficiency and number of inputs and outputs used. The input and output factors were thus carefully selected to reflect the capacity and scope of sampled facilities in clinical and nonclinical activities. Below are the inputs and output factors:

Input factors

1. Clinical staff (CS), the total number of clinical staff employed in the clinic or hospital.
2. Support staff (SS), the total number of support staff employed in the clinic or hospital.
3. Beds (B), the number of existing patient beds within the clinic or hospital ready for use.
4. Consulting rooms (CR), total number of consulting rooms in the clinic or hospital.

Output factors

1. Antenatal and postnatal visits (Y_1), number of antenatal and postnatal visits within a year.
2. Outpatient visits (Y_2), the number of outpatient visits within a year.
3. Deliveries (Y_3), the number of deliveries within a year.
4. Family planning (Y_4), the number of family planning within a year.

$$Y_i \text{ where } i = 1, 2, 3, 4$$

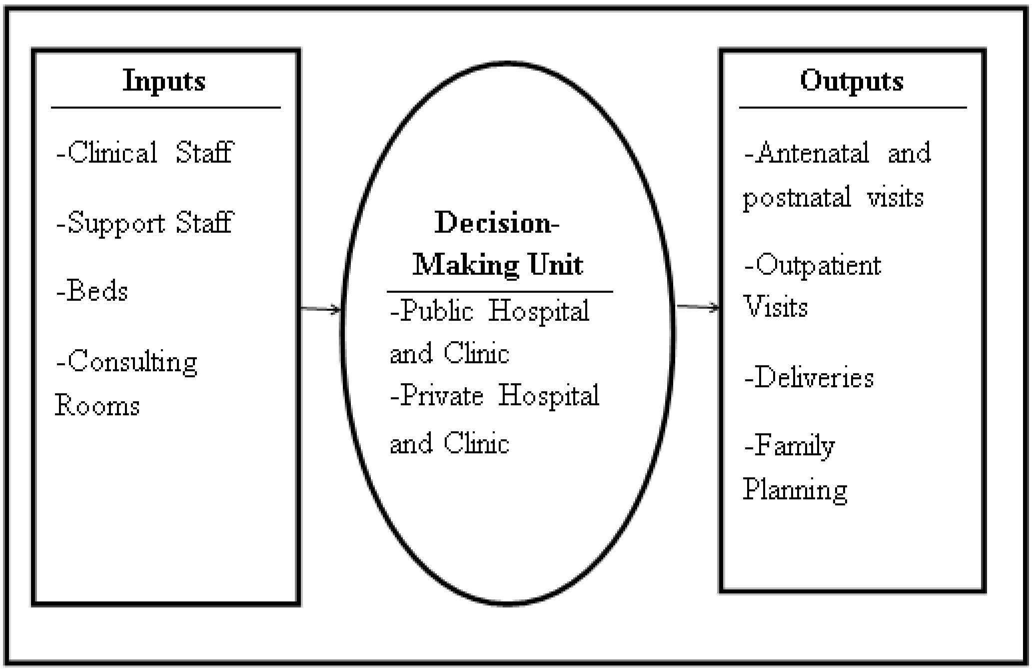

Figure 3: Inputs, Process and Outputs for Clinics and Hospitals

Source: Field survey, (2017)

The study used DEA approach since it allows the measurement of relative efficiency when decision-making units (in this case public and private clinics and hospitals) have multiple inputs and multiple outputs. It is very important to select input and output variables in studies applying DEA. Clinics and hospitals turn inputs into outputs (health services) in the production process. It is widely acknowledged that the ultimate output in the production process of health facilities is improvement in population health. However, due to the measurement complexities and the availability of data for this type of analysis, it becomes difficult to assess the improvements in population health attributable to healthcare. Therefore, intermediate outputs are generally used as a preferred choice. Figure 3 depicts the relationship between health system inputs, the production process, and the outputs or results.

Theoretical Model

Existing measures of efficiency are based on a variety of methodologies. Each of these methods compares outputs to inputs across units within some setting. For example, they might compare discharges to labour hours within hospitals. The methods differ in their assumptions and their ease of implementation. Principal methods include ratios, data envelopment analysis (DEA), stochastic frontier analysis (SFA), regression-based approaches, and Malmquist and other index numbers.

DEA uses complex mathematical-programming techniques to produce an efficiency score for each unit analysed (Brukner, 2001; Brown & Hoover, 1991). It can account for multiple inputs and outputs without requiring any assumptions about the relationship among them. According to Capettini and Corey (1985), DEA does assume that all inputs and outputs are included in the analysis, and the results may be unreliable if this assumption is not correct. Like ratios, DEA can be used to measure technical or productive efficiency. If cost data are available, differences in technical efficiency can be distinguished from differences in the costliness of the mix of productive inputs (e.g., the balance between physician and nursing labour). DEA is typically "deterministic," that is, this method usually ignores random noise in inputs and outputs as a potential source of variation in efficiency scores.

SFA is an econometric technique that allows for such "stochastic" noise (Castello et al., 2003). In an analysis of technical efficiency, a particular relationship between outputs and technical inputs is assumed; productive efficiency can be analysed by specifying the relationship between costs and multiple outputs (if desired). Inefficiency is distinguished from measurement error through assumptions about the distribution of each. In particular, measurement error can lead observed output to be either higher or lower than expected based on observed inputs, while inefficiency can only lead output to be lower than expected. If these assumptions are valid, SFA can be more informative about inefficiency across units than DEA. SFA, like DEA, can be unreliable if some inputs or outputs are excluded.

Chan et al. (2002) identified that there are regression-based approaches. For example, in corrected ordinary least squares (COLS), technical efficiency is analysed by regressing an output on productive inputs. Like SFA, COLS makes an assumption about the relationship between inputs and outputs. COLS is easier to implement, but at the cost of making more restrictive assumptions about the relationship between inputs and outputs across units (Chang et al., 1998). Productive efficiency can also be analysed with regression-based approaches.

Application of DEA

Data Envelopment Analysis (DEA) has proven to be a powerful tool for the analysis of the magnitude and cause of inefficiency. It is now widely applied to performance analysis in such diverse fields. As already indicated in this study, DEA uses linear programming to establish an "efficiency frontier" from the most efficient utilities from a set of data. As depicted in Figure 4, a boundary is created by linearly linking the observed performance of the best performing companies in the sample, and is determined by the relationship between their inputs and outputs.

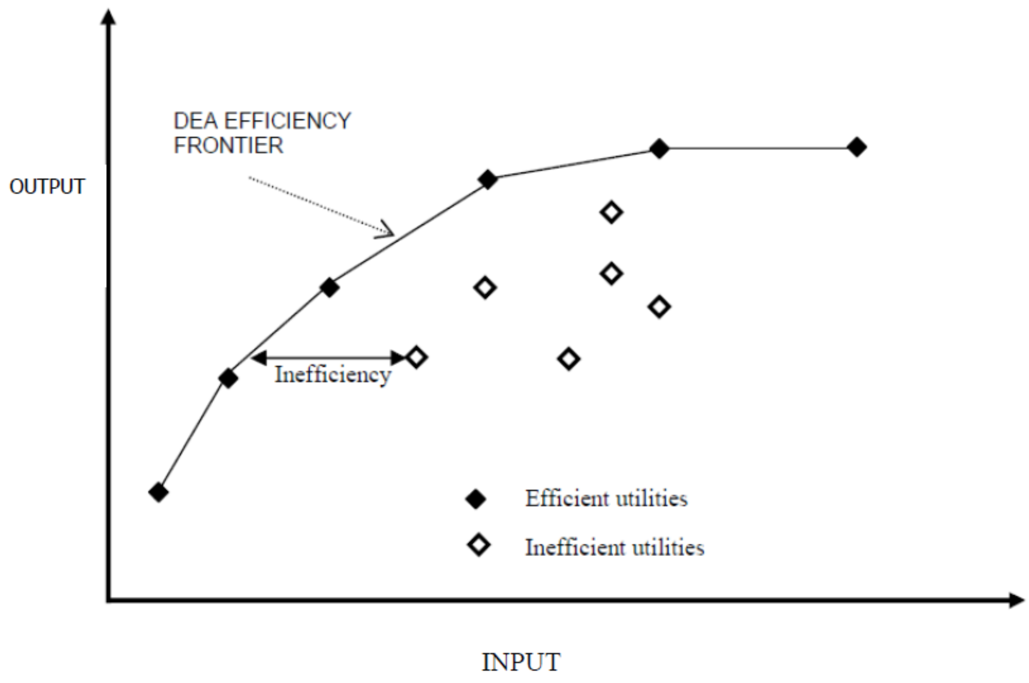

Figure 4: DEA Efficiency Frontier Diagram

Source: Charnes, W., et al. (2006). Introduction to data envelopment analysis and its uses: With DEA-solver software and references. New York: Springer, 81.

Utilities that form the efficiency frontier use the minimum quantity of inputs to produce the same quantity of outputs as other, similar utilities. DEA is a comparatively new "data oriented" approach for assessing the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. DMU refers to any entity that is to be evaluated in terms of its abilities to convert inputs into outputs. For instance DEA applications have used DMUs such as hospitals, US Air Force wings, universities, cities, courts, business firms, and others, including the performance of countries, regions and others.

Using DEA model, researchers are required to formulate the problem into mathematical expression. The mathematical formulation of DEA technique consists in the solution of a set of linear programming models (Charnes et al., 1978) aimed at maximizing the efficiency of decision making units (DMUs).

Inputs are elemental factors or resources (e.g. labour, capital, human resource) that significantly affect the consumption of available resources used in an institution. Outputs are factors that trigger the quantity of outcomes obtained from available resources (eg service and production) being processed in an institution.

Estimation Techniques

This study applies the DEA approach in measuring the technical efficiency of private and public clinics and hospitals in the Central Region of Ghana. As Jacobs, Smith & Street (2006) mention, advocates of DEA would argue that the problems of providing a prior specification of functional form can be avoided by applying a non-parametric technique. Consequently, DEA is highly flexible, the frontier moulding itself to the data. DEA has been recommended for evaluating the clinic efficiency in settings with inefficient health-sector information and particularly inappropriate data availability on prices of inputs (Worthington, 2004). It was essential in this study to use an approach suitable for measuring the technical efficiency of hospitals that use multiple inputs to produce multiple outputs. In contrast to parametric methods such as SFA, the non-parametric properties of DEA provide that required flexibility.

DEA, as an analytical tool, has flexibility in handling multiple inputs and outputs, which make it suitable for measuring the efficiency of clinics and hospitals that use multiple inputs to produce multiple outputs. However, it produces results, which are sensitive to measurement error, and it measures the efficiency relative to the best practicing private and public clinics and hospitals within the sample included in the study. One shortcoming of DEA is that it captures the best among the sample but we do not know if these best private and public clinics and hospitals can perform better. This is because DEA estimates the relative efficiency of a clinic or hospital and compare to its peers but not the absolute efficiency such as a theoretical maximum efficiency of a clinic or hospital.

DEA results can be used by decision makers and administrators as inputs in making informed decisions regarding the planning, allocation, and utilization of resources. The information generated by DEA on output inefficiencies and excess inputs can be substantially utilized for the monitoring of the performance of private and public clinics and hospitals and as well as the health systems.

The Constant Returns to Scale DEA model

Charnes et al. (1978) proposed a DEA model based on constant returns to scale (CRS) and an input orientation approach. They specified a fractional linear programme for each decision-making unit (DMU) that computes the relative efficiency and compared it to all the other observations in the sample. The exposition can be explained by means of an illustration as follows. Suppose that there are data on K inputs and M outputs on each of N decision-making units. The data for all the DMUs are given by KxN input matrix, X, and the MxN output matrix, Y. DEA is introduced by means of ratio and for each DMU (thus, a clinic or hospital), one seeks to obtain a measure of the ratio of all outputs over all inputs, which takes the following form: $\frac{u'y_i}{v'x_i}$, where u' is an Mx1 vector of output weights and v' is a Kx1 vector of input weights. Selection of optimal weights involves solving the following mathematical programming problem:

$$Max_{\ u,v}\left(\frac{u'y_i}{v'x_i}\right)$$

Subject to (1)

$$\frac{u'y_j}{v'x_j} \le 1 \quad \text{j=1, 2… N}$$

$$u, v \ge 0$$

The mathematical programming problem entails finding values for u' and v', such that the efficiency measure of the ith clinic or hospital is maximized subject to the constraint such that the overall efficiency measures must be equal to or less than unity. However, formulation (1) has the disadvantage of having an infinite number of solutions. For example, ($u*, v*$) and ($\alpha u*, \alpha v*$) are solutions for the same problem. To deal with this problem one can impose the constraint $v'x_i = 1$ which yields the following linear programming problem:

$$Max\ u, v[u'y_i]$$

Subject to

$$v'x_i = 1$$

$$u'y_j - v'x_j \leq 0 \text{ j} = 1, 2\ldots \text{N} \tag{2}$$

$$u, v \geq 0$$

This form is known as the multiplier form of the linear programming problem. An equivalent envelopment form of this linear programming model can be derived by means of duality (Coelli, 1996):

$$Min_{\theta\,\lambda}\,\theta$$

Subject to

$$-y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0 \tag{3}$$

$$\lambda \geq 0$$

θ is a scalar and λ is an Nx1 vector of constants. This envelopment form consists of fewer constraints than the multiplier form and thus, it is the generally preferable form to solve. The value of θ obtained is the efficiency score for a clinic or hospital and it has to satisfy $0 \leq \theta \leq 1$. According to Farrell's (1957) definition, a value of 1 is a point on the production frontier which shows a technically efficient decision making unit.

The Variable Returns to Scale DEA model

The model by Charnes et al. (1978) assumes constant returns to scale (CRS). Returns to scale refer to the changes in output as a result of change in all inputs by the same proportion. CRS implies that output changes by the same proportion as the change in inputs and thus the size of clinics and hospitals becomes irrelevant when measuring efficiency since all clinics and hospitals are deemed to be operating at their best scale size. However, size of a clinic or hospital is an important factor in this analysis and thus the assumption of variable return to scale (VRS), which allows the level of outputs to inputs to vary with the size of the clinic or hospital, is more binding. Banker et al. (1984) added an intercept term to the Charnes et al. (1978) model to take care of the variable returns to scale.

The CRS linear programming problem can be modified to account for VRS by adding the convexity constraint: $N1'\lambda = 1$, where N1 is an Nx1 vector of ones and provides technical efficiency scores which are equal to or greater than those obtainable by the CRS model.

Thus the model becomes:

$$Min_{\theta\,\lambda}\,\theta$$

Subject to

$$-y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$N1'\lambda = 1 \qquad (4)$$

$$\lambda \geq 0$$

This approach provides technical efficiency scores which are equal to or greater than those obtainable by the CRS model since they form a convex hull of intersecting planes that envelope the data points more tightly than the CRS canonical hull.

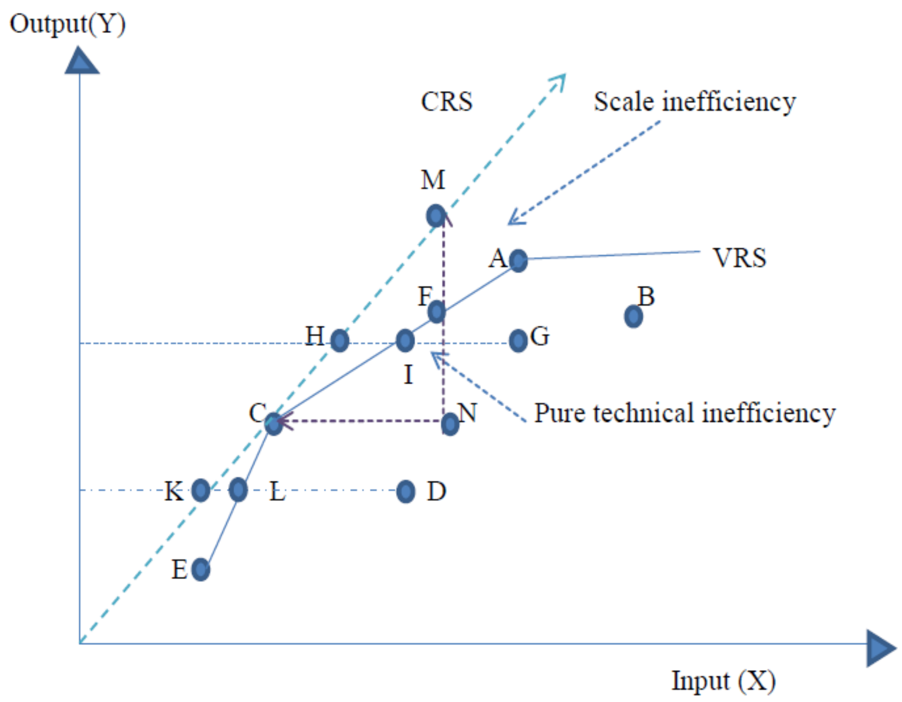

Figure 5: The difference between the CRS and VRS production frontiers

Source: Charnes, W., et al. (2006). Introduction to data envelopment analysis and its uses: With DEA-solver software and references. New York: Springer, 81.

Through the use of Figure 5, it is easy to observe that the only hospital that appears to be Charnes Cooper Rhodes (CCR)-efficient and Banker Charnes Cooper (BCC)-efficient is hospital “C”. Consequently, this is the only hospital with no “scale effects” in the assessment of its technical efficiency scores. The area representing the difference between the straight line (CCR model) and the curve (BCC model) indicates the “scale effects” in assessing technical efficiency. For example, the technical efficiency of hospital “G” is calculated to be segment IG according to the BCC model and segment HG according to the CCR model.

A similar observation can be made for hospital "D". However, on this occasion, the Increasing Return to Scale (i.e. the over-proportional increase in output due to proportional increase in inputs) would offset (compensate for) part of the scale inefficiency. Nonetheless, unlike the CCR model, the "input-oriented" and "output-oriented" approaches would not generate the same efficiency scores. This is due to the fact that the two approaches conceptualise the 'returns to scale' differently.

Empirical Specification of the CRS and VRS Model in DEA

Charnes et al. (1978) proposed a DEA model based on constant returns to scale (CRS).

$$\max \frac{\delta[Y_1 + \beta_2 Y_2 + \beta_3 Y_3 + \beta_4 Y_4]}{\gamma[CS + SS + B + CR]} \qquad (5)$$

Subject to

$$\frac{\delta[Y_{1_j} + Y_{2_j} + Y_{3_j} + Y_{4_j}]}{\gamma[CS_j + SS_j + SS_j + CR_j]} \leq 1$$

Where $\delta, \gamma \geq 0$

Given that

$$\left[CS_j + SS_j + SS_j + CR_j\right] = 1$$

We get

$$\max \frac{\delta}{\gamma}\left[Y_{1_j} + Y_{2_j} + Y_{3_j} + Y_{4_j}\right] \qquad (6)$$

Subject to

$$\delta\,[\,Y_{1_j} + Y_{2_j} + Y_{3_j} + Y_{4_j}]$$

Where Y_1 represents antenatal and postnatal visits;

Y_2 represent number of outpatient visits;

Y_3 represents number of deliveries within a year;

Y_4 represents number of family planning;

CS represents number of clinical staff;

SS represents number of support staff;

B represents number of existing beds; and

CR represents number of consulting rooms

Econometric Analysis of the Determinants of Inefficiency

The (in) efficiency scores obtained from the DEAP software stated whether a particular decision making unit is technically efficient or not. But there are institutional and environmental factors that cause technical inefficiency and are beyond the control of managerial discretions. To examine how these factors affect the (in) efficiency of decision making units, the DEA efficiency scores were analysed by regressing them against some characteristics of the DMUs using the simple ordinary least square.

Since the dependent variable (efficiency scores) is continuous between one and zero, it was not advisable to apply logistic regression, and also since the efficiency scores are bounded from above at one, using OLS model would lead to biased results. Up to this level, DEA efficiency scores were to be transformed into efficiency scores and left censored at zero using the formula:

$$\text{Inefficiency score} = \left(\frac{1}{\text{DEA Score}}\right) - 1$$

$$\text{Ineff} = \alpha + \beta_1 APV + \beta_2 OPV + \beta_3 DV + \beta_4 FP + \varepsilon_i$$

Where

APV = Antenatal and Postnatal Visit

OPV = Outpatient Visit

DV = Delivery Visit

FP = Family Planning

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

The results of the study are presented and discussed in this chapter. The main objective of the present study is to conduct a comparative analysis of the technical efficiency of private and public clinics and hospitals in the Central Region of Ghana. Under this chapter the results of the descriptive statistics of all input and output variables, DEA efficiency results, results slacks obtained from the DEA model and linear regression test are presented and discussed. These results are discussed in relation to the objectives of the study.

Descriptive Statistics for Private Clinics and Hospitals

With regards to ownership, Table 1 gives a summary of the inputs and outputs variables of the clinics and hospitals privately owned. The highest input was the licenced beds of about 32. This is followed by the number of registered nurses of 15 and the remaining variables being less than 10.

Table 1 as well indicates that for the year under review, outpatient visits were about 11,381. This was the highest output variable recorded for the private clinics and hospitals. This is followed by the number of antenatal visits which on the average was 2,883. Averagely, inpatients visits and deliveries were 1,378 and 649 respectively. The remaining outputs variables were less than 4.

Table 1: Descriptive Statistics for Private Hospitals and Clinics

Variables	Obs	Mean	Std. Dev.	Min	Max
Inputs					
Doctors	14	2.79	3.29	0	12
Dentists	14	0.21	0.43	0	1
Other Trainees	14	6.14	11.01	0	31
Registered Nurses	14	15.43	25.83	0	91
No of Administrators	14	1.5	1.16	1	5
Total Licensed Beds	14	32.43	31.64	4	130
Consulting Room	14	3.14	2.28	1	10
Outputs					
Outpatient Visits	14	11381.14	21840.15	0	81720
Deliveries	14	649.71	848.92	0	2496
Antenatal	14	2883.43	4094.49	0	10740
Family Planning	14	2.64	1.28	1	5
Vaccinations	14	3.14	1.23	1	5
Immunization	14	2.79	1.48	1	5
Primary Care	14	2.93	1.49	1	5
Inpatient Visits	14	1378.5	2255.6	0	8065

Source: Field survey, (2017)

Descriptive Statistics for Public Clinics and Hospitals

On the other hand, Table 2 as well depicts the quantitative summaries of the input and output variables of the public clinics and hospitals in the study area. The public facilities had averagely 45 licenced beds. Additionally, the mean number of doctors was 2. With regards to registered nurses the public had 36 and with the remaining input variables being less than 4.

Table 2: Descriptive Statistics for Public Hospitals and Clinics

Variables	Obs	Mean	Std. Dev.	Min	Max
Inputs					
Doctors	20	2.5	2.12	0	9
Dentists	20	0.5	0.83	0	2
Other Trainees	20	2	3.01	0	10
Registered Nurses	20	36.6	56.85	0	244
No of Administrators	20	1	0.32	0	2
Total Licensed Beds	20	45.95	61.26	0	234
Consulting Room	20	3.4	2.68	0	11
Outputs					
Outpatient Visit	20	58116	167967.1	0	764064
Deliveries	20	1259.4	2854.71	0	12780
Antenatal	20	6024	11098.69	0	46980
Family Planning	20	3.9	0.85	3	5
Vaccinations	20	3.95	0.83	2	5
Immunization	20	4.1	0.79	2	5
Primary Care	20	3.2	1.51	1	5
Inpatient Visits	20	3813.4	9448.73	0	42340

Source: Field survey, (2017)

Generally, public clinics and hospitals had quite higher variable outputs. The analysis indicates that the mean number of outpatient visits have been the highest among the selected output variables. Public outpatient visits were about 58,116 (Table 2). The public as well had 6,024 and 3,813 antenatal visits and inpatient visits respectively for the period of study. Whiles the mean number for the deliveries was 1,259, the remaining output variables were less than 5.

Descriptive Statistics of the Background Study

The charts below give descriptions of the study variables. They also include some other determinants of clinic and hospital input which are not part of the input variables. Figures 6 and 7 depict the educational level of the administrators in the various clinics and hospitals based on their ownership. It is observed from Figure 6 that the public clinics had higher number of administrators with tertiary and professional background than the private-owned clinics. With this level of composition in the labour of public clinics, one would have expected to have them to have higher efficiency but rather from the technical efficiency analysis, the private clinics were noted to be technically efficient.

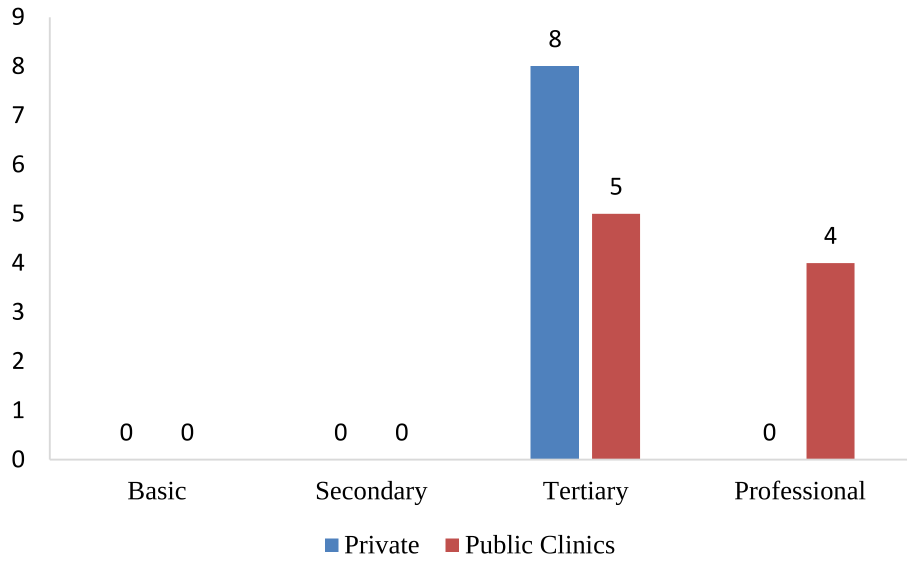

Figure 6: Educational Status of Private and Public Clinics

Source: Field survey, (2017)

From the hospital perspective, a similar case is also noted. The study in the region clearly indicate that the public-owned hospitals were much endowed with more administrators with more tertiary and professional qualifications as compared to their private counterparts (Figure 7). However, as earlier mentioned for the clinics, the public hospitals also did not efficiently produce output to commensurate with the level of qualified administrators they have.

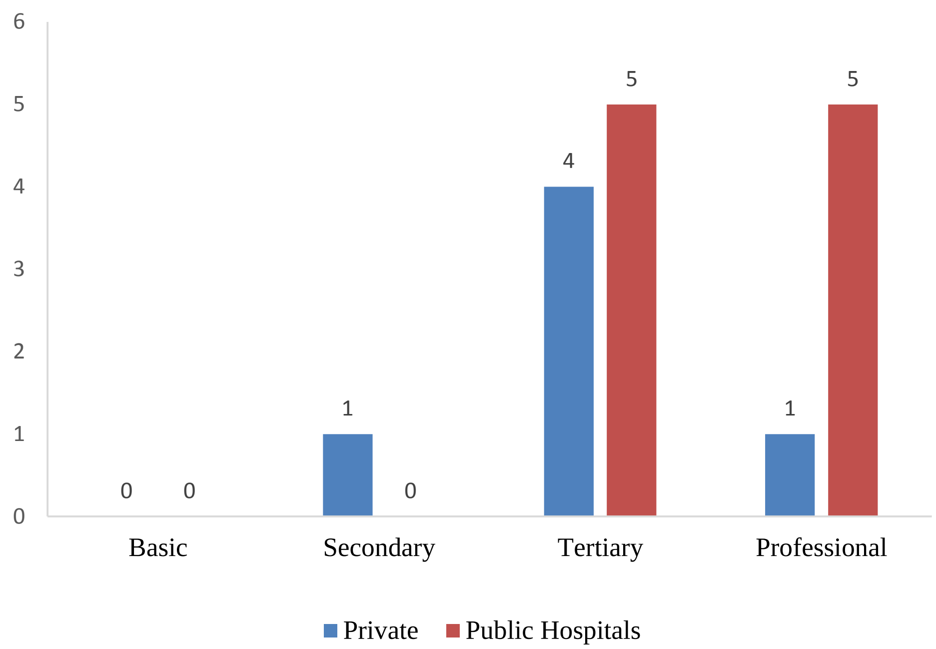

Figure 7: Educational Status of Private and Public Hospitals

Source: Field survey, (2017)

Table 3: Descriptive Statistics of working experience of Administrators

Experience of	Clinics		Hospitals	
Administrators	Private	Public	Private	Public
less than10 years	6	6	4	5
10-20 years	1	2	1	4
21-30 years	1	1	0	0
above 30 years	0	0	1	1

Source: Field survey, (2017)

Further to this, the working experience of the administrators of both clinics and hospitals were ascertained. This was based on the number of years an administrator has worked with the facility. According to Table 3, both the private and public clinics had 6 administrators who have worked for less than

10 years. It is also observed that this category forms more than 65% of the total administrators in the clinics. Whereas the private clinics have 2 administrators who have working experience from 10 to 30 years, the public ones had 1 in addition who fall in the same category of years. The experience acquired over a period of years is also essential to the technical efficiency of a clinic. Considering the administrators who have worked for less than 10 years in the hospitals, it was also observed that the private hospitals had 4 as compared to 5 for the public ones. The table further depicts that, those within the ranges of 10 and 20 years were 1 and 4 for the private and public hospitals respectively. Interestingly, it was noted that both ownerships for the hospitals had 1 each for administrators who have worked for more than 30 years in their facilities. This may therefore suggest that the public hospitals had more managers who had more years of working experience than the private facilities. However, the analysis of technical efficiency scores indicates that this endowment of years of working experience do not reflect in the input and output mix.

Descriptive Statistics for Hospitals

Input Variables for Hospitals

Table 4 below provides a summary of the descriptive statistics from the sample of 16 private and public hospitals in the study area. Findings indicate there are some similarities in specific input variables and as well as some level of variation in the mean input variables between the private and the public hospitals. The mean number of doctors remains close to 3 and 4 for private and public hospitals respectively. The public hospitals had almost mean number of 1 for dentist input variable as compared to private ones having close to 0. The private hospitals recorded about 6.4 times greater mean number of other trainees than the public hospitals. The public hospitals in 2016 saw 1.93 times as many registered nurses than the private hospitals in the study area. The variation in the mean number ranges from close to 24 in the private hospitals to 4 in the public hospitals. Concerning the number of other support staff input variable, the public hospitals further recorded close to 1 mean number as against close to 0 for their private counterparts. Regarding the number of administrators, the private hospitals manifested twice of that of the public ones in the study. Whereas the variation in the mean number of licensed beds ranges from 47 in the private hospitals to 57 beds in the public hospitals, there is no significant variation for consulting room input variable for both the private and the public hospitals. This suggests that public hospitals are larger, in terms of resource endowment, than the private ones. For instance, the public hospitals have 1.21 times more licenced beds than the private ones.

Table 4: Summary Statistics of Variable Inputs for Hospitals

Variable	Ownership	Obs	Mean	Std. Dev.	Min	Max
Doctor	Private	6	3.83	4.02	2	12
	Public	10	3.4	2.41	0	9
Dentists	Private	6	0.17	0.41	0	1
	Public	10	0.9	1	0	2
Other Trainees	Private	6	9.67	14.68	0	31
	Public	10	1.5	3.37	0	10
Registered nurses	Private	6	23.5	33.73	1	91
	Public	10	45.4	29.36	0	98
No other Support staff	Private	6	0.33	0.52	0	1
	Public	10	1	1.89	0	6
No of Administrators	Private	6	2.17	1.6	1	5
	Public	10	1.1	0.32	1	2
Total Licenced beds	Private	6	46.67	42.34	10	130
	Public	10	56.5	51.7	0	162
Consulting room	Private	6	4.17	3.06	2	10
	Public	10	4.5	2.99	2	11

Source: Field survey, (2017)

Output Variables for Hospitals

Table 5 below gives a summary of the output variables of both the sampled private hospitals and the public ones in the study area. Generally, the public hospitals manifested higher outputs in all the selected variables for analysis. The public hospitals had about 4.16 times more average number of outpatient visits than the private hospitals. While the public hospitals had about 1.41 times more for family planning than the private ones, their immunization in terms of output was almost the same as that of the private. Similarly, public hospitals recorded about 3.6 times more in average number of deliveries for the study period. Furthermore, both the antenatal and postnatal visits for the public hospitals were substantially greater than the private ones. The antenatal and postnatal visits for the private hospitals formed about 35.4% and 14.5% respectively of the public hospitals' outputs. It is obvious from the analysis that the public hospitals produced more outputs than the private counterparts. This is not the case for the clinics. The private clinics manifested more outputs, which was proportionate to the level of inputs they had.

Table 5: Summary Statistics of Variable Outputs for Hospitals

Variable	Ownership	Obs	Mean	Std. Dev.	Min	Max
Outpatient Visits	Private	6	25822	33168.08	0	81720
	Public	10	107613.6	232140.63	1392	764064
Deliveries	Private	6	642	877.09	0	2244
	Public	10	2368.8	3812.98	168	12780
Family Planning	Private	6	2.83	0.98	1	4
	Public	10	4	0.94	3	5
Immunization	Private	6	3.5	1.05	2	5
	Public	10	4.2	0.79	3	5
Antenatal Visits	Private	6	3966	4756.21	0	10740
	Public	10	11176.8	14211.44	168	46980
Postnatal Visits	Private	6	758	840.46	0	2184
	Public	10	5210.4	7633.21	0	24504
Primary Care	Private	6	3.5	1.64	1	5
	Public	10	3.9	1.29	1	5

Source: Field survey, (2017)

Efficiency results from the DEA Model

Efficiency is measured on a scale of 0 to 1, where a value of 1 indicates the DMU is relatively efficient, and a value less than 1 indicates the unit is inefficient. The efficiency score of a unit will vary according to the factors and DMUs included in the analysis.

Technical efficiency scores for private hospitals were observed as presented in the table below. The technical efficiency scores for the private hospitals were moderately high as demonstrated by their individual scores ranging from 0.81 to 1. Out of the 6 sampled private hospitals, 50% manifested technical efficiency score of 1 and the remaining 3 were close to efficiency. Table 6 depicts the aggregate technical efficiency score of 0.94 which confirms the existence of a wide-spread of technical efficiency with the private hospitals in the study area. The mean CRS technical efficiency score of 0.79 depicts that most of the private hospitals were moderately close to efficiency. However, only 2 private hospitals out of the 6 were operating at the optimal level. This implies that 4 private hospitals could have further increased their outputs in terms of outpatients with the current level of inputs without compromising their present efficiency. When the effect of scale/hospital size was excluded the VRS average technical efficiency score was 0.94. As indicated in Table 6, 4 private hospitals manifested decreasing returns to scale. This implies that these private hospitals may be too large for the volume of activities that they undertake and therefore, may experience diseconomies of scale.

Table 6: Efficiency Scores of Private Hospitals

Hospital	Technical Efficiency	crste	vrste	scale	
1	1	1	1	1	-
2	0.865	0.83	0.87	0.95	drs
3	0.813	0.78	0.81	0.96	drs
4	0.95	0.82	0.95	0.86	drs
5	1	1	1	1	-
6	1	0.33	1	0.33	drs
Mean	0.94	0.79	0.94	0.85	

Source: Field survey, (2017)

Note: crste = technical efficiency from CRS DEA

vrste = technical efficiency from VRS DEA

Scale = scale efficiency = crste/vrste

The technical efficiency scores for the public hospitals were stable as demonstrated by very highly significant Spearman's rank correlation coefficients ranging from 0.87 to 1. Table 7 depicts the aggregate technical efficiency score of 0.99 which implies the presence of a wide-spread of high technical efficiency with the public hospitals in the study area. The constant returns to scale (CRS) model indicates a high level of technical efficiency in the public hospitals included in the study. The mean CRS technical efficiency score is 0.92, implying that on average these public hospitals were highly close to efficiency. However, they could have further increased their outputs in terms of outpatients by about 8% with the current level of inputs without compromising their current efficiency. The VRS model gives the level of pure technical efficiency when the effect of scale/hospital size has been excluded. Thus, the VRS technical efficiency score as shown in Table 7 indicates high efficiency level of 0.99. Out of the 10 public hospitals 50% manifested decreasing returns to scale (diseconomies of scale) implying that they were inefficiently large given their current scale of operation or production. In this case, a 1% increase in all inputs (doctor, nurse and bed) leads to less than 1% increase in outputs (outpatient visits, deliveries and family planning).

Table 7: Efficiency Scores of Public Hospitals

Firm	Technical Efficiency	crste	vrste	scale	
1	1	0.98	1	0.98	drs
2	1	1	1	1	-
3	1	1	1	1	-
4	1	1	1	1	crs
5	1	1	1	1	-
6	0.865	0.83	0.87	0.95	drs
7	1	0.86	1	0.86	drs
8	1	0.78	1	0.78	drs
9	1	1	1	1	-
10	0.993	0.76	0.99	0.77	drs
Mean	0.99	0.92	0.99	0.93	

Source: Field survey, (2017)

Note: crste = technical efficiency from CRS DEA

vrste = technical efficiency from VRS DEA

Scale = scale efficiency = crste/vrste

Technical efficiency scores for hospitals were also observed to have variation by ownership as presented in Figure 8 below. The mean technical efficiency score of public hospitals is more than that of the private ones. This therefore suggests that the public hospitals in the sample area are technically efficient than their private counterparts. Comparatively, the private hospitals manifested more decreasing returns to scale than the public-owned hospitals. In other words, 66% of the private hospitals were inefficiently large given their current scale of operation or production as against 50% for the public ones. This study is in line with Hollingsworth (2003) in his meta-analysis of

317 publications which concludes that public provision of healthcare services may be potentially more efficient than private. It is further supported by Jehu-Appiah et al. (2014) in their analysis of ownership and technical efficiency of hospitals and concluded that private hospitals exhibited the highest level of inefficiency compared to public health facilities.

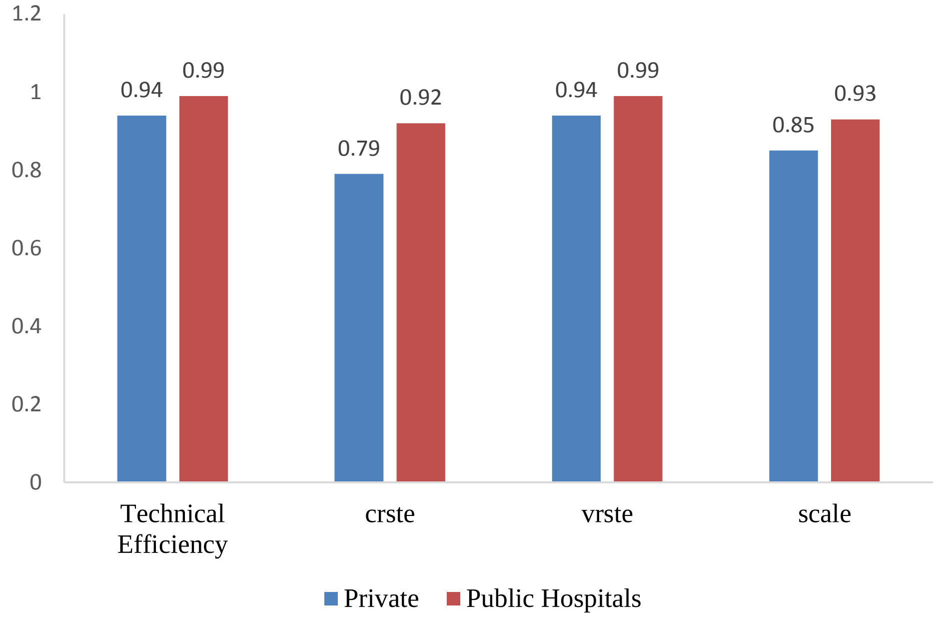

Figure 8: DEA Model for Private and Public Hospitals

Source: Field survey, (2017)

Slack Results

Slack analysis was made to determine the inefficient clinics and hospitals to see how they would need to change regarding their input and output variables in order to help them reach the efficiency frontier, which is the optimal level of efficiency. The slack analysis provides additional insights about the magnitude of inefficiency for the under-performed clinics and hospitals. The magnitude of inefficiency is given by quantity of deficient output produced (output slacks) and/or excess resources used (input slacks) by inefficient clinics or hospitals. If a clinic or hospital does not have slacks in inputs, then it implies that the clinic or hospital has utilized its inputs efficiently. The non-zero slacks in inputs show the over-utilization and non-zero slacks in outputs show under-production. As a corrective action, inputs need to be decreased while outputs need to increase. Examining the slack analysis for each clinic or hospital shows opportunities for improvement in inputs or outputs or both.

Input Slack for Hospital

Table 8 gives the slack results for the 6 sampled private hospitals in the study area. It indicates that only 1 of the private hospitals was inefficient. This implies that only one private hospital out of the 6 can decrease its input variables (clinical staff and licensed beds) by 1 each to operate as efficiently as its counterparts.

Table 8: Input slacks of Private Hospitals

Hospital	Clinical Staff	Support Staff	Beds	Consulting Rooms
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	1	0	1	0
5	0	0	0	0
6	0	0	0	0
Mean	0.17	0	0.17	0

Source: Field survey, (2017)

On the other hand, the number of public hospitals, which could decrease their inputs to become efficient, was 5 (Table 9). This represents 50% of the sampled 10 public hospitals in the region. The mean numbers for the excess input variables were as follows: Clinical staff 0.6, Support Staff 0.41, Beds 0.03 and consulting rooms 0.43.

Table 9: Input slacks of Public Hospitals

Hospital	Clinical Staff	Support Staff	Beds	Consulting Rooms
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0.56	0	0
5	0	0	0.29	4.29
6	0	0.56	0	0
7	6	0	0	0
8	0	3	0	0
9	0	0	0	0
10	0	0	0	0
Mean	0.6	0.41	0.03	0.43

Source: Field survey, (2017)

The public hospitals had excess inputs in all the selected input variables as compared to their private counterparts for the study. In terms of the magnitude, the private hospitals had about 16.6%, which needed to reduce inputs to attain efficiency as against 50% for the public ones. Examining the slack analysis for both ownerships shows that the public hospitals have more prospects for improvement in their input variables in order to attain the optimal level of efficiency (Figure 9).

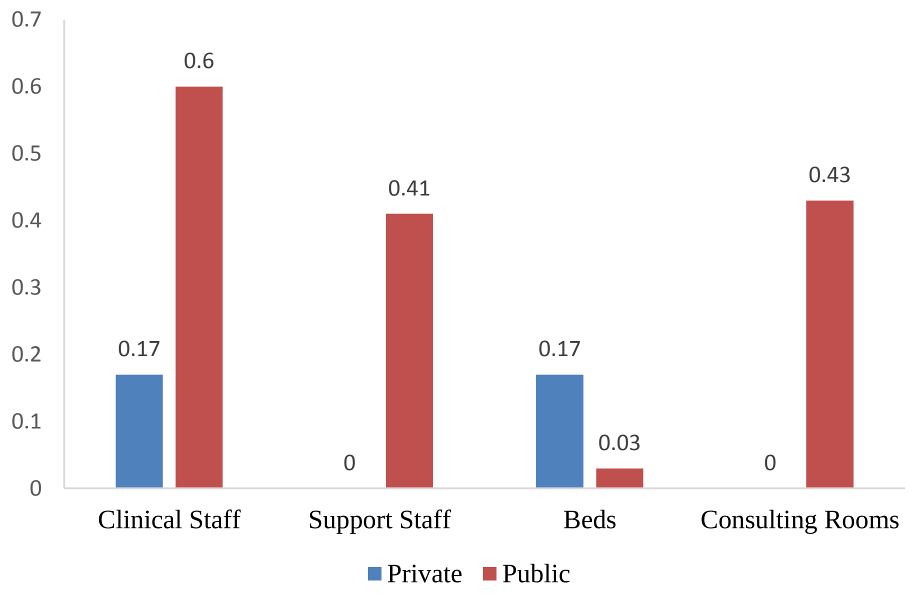

Figure 9: Slack Distribution for Private and Public Hospitals

Source: Field survey, (2017)

Output Slack for Hospitals

Efficiency scores alone do not reveal the full magnitude of inefficiency. For example, a high technical efficiency score associated with large slack variables for a clinic or hospital does not necessarily indicate better performance than a low efficiency score with small or zero slacks.

Generally, it was noted that, with the exception of the 4^{th} privately owned hospital, all the remaining had no slack in the region (Table 10). Slacks exist only for those hospitals identified as inefficient. It is noted that only the 4^{th} hospital is required to increase its antenatal and postnatal visits by 0.42 to push to the efficient target.

Table 10: Outputs slacks of Private Hospitals

Hospital	Antenatal and Postnatal Visits	Outpatient Visits
1	0	0
2	0	0
3	0	0
4	0.42	0
5	0	0
6	0	0
Mean	0.07	0

Source: Field survey, (2017)

From the public hospital perspective, it was observed that 5 out of the 10 have to augment their output to be efficient. According to Table 11, the 7th public hospital is required to increase its outpatient visits by 3,766. The remaining 4 public hospitals as well indicated some level of underproduction in the antenatal and postnatal visits for the period of the study. This clearly gives an indication that the public hospitals have more capacity to increase their outputs as compared with the private-owned hospitals.

Table 11: Outputs slacks of Public Hospitals

Hospital	Antenatal and Postnatal Visits	Outpatient Visits
1	0	0
2	0	0
3	0	0
4	2.38	0
5	3.05	0
6	2.38	0
7	0	3766
8	0	0
9	0	0
10	16.29	0
Mean	2.41	376.6

Source: Field survey, (2017)

Efficiency Determinants of Hospitals

Regarding the hospitals in the area, the analysis showed that operating week and public hospital access variables negatively affected the technical efficiency of private and public hospitals in the region (Table 12). However, the public ownership and the experience of the administrators had positive significant influence on the technical efficiency of the private and public hospitals.

Table 12: Determinants of efficiency of Private and Public Hospital

VARIABLES	Parameter	Coefficient	Standard errors	P-Value
Constant	δ_0	1.023***	0. 174	0.000
Operating Week	δ_1	-0.013	.024	0.593
Emergency Dept.	δ_2	-0.000***	0.000	0.000
Public Ownership	δ_3	0.019	0.025	0.451
Public Hospital Access	δ_4	-0.042	0.048	0.409
Experience of Administrators	δ_5	0.012	0. 011	0.317
R^2		0.76		
No. of observations		16		

Source: Field survey, (2017)

Table 13 indicates that, the public ownership had a positive impact on the technical efficiency of selected hospitals in the study area. The coefficient gives a positive value of 0.019.

Table 13: Level of efficiency of Private and Public Hospitals

VARIABLES	Coefficient	Standard Error	P-Value
Constant	0.927***	0.032	0.000
Public Ownership	0.019	0.041	0.651
R^2	0.02		
No. of observations	16		

Source: Field survey, (2017)

Descriptive Statistics for Clinics

Input Variables for Clinics

This section ascertains the characteristics of clinics by comparing the efficiencies of different ownership's results. Hence, the research is less interested in identifying single winners or losers, as the focus is identified as groups of best and worst performers. The ownership type within the clinic that affects the composition of the best and worst performing clinics is evaluated, which subsequently characterises extreme performers. Table 14 below provides a summary of the descriptive statistics from the sample of 18 private and public clinics in the Central Region of Ghana. Findings indicate there are some variations in the mean input variables by ownership. The mean number of doctors remains close to 2 for both private and public clinics. Again, both the private and public clinics had almost mean number of 0 for dentist input. The private clinics recorded 1 greater mean number of other trainees than the public clinics. The public clinics in 2016 saw thrice as many registered nurses than the private clinics in the study area. The variation in the mean number ranges from 9 in the private clinics to 28 in the public clinics. Regarding the number of other support staff input, the public further recorded close to 5 mean number as against close to 0 for their private counterparts. There was no variation on the number of administrators for both ownership as they all had close to 1. Whereas the variation in the mean number of licensed beds ranges from 22 in the private clinics to 35 beds in the public clinics, there is no variation for consulting room input for both the private and the public. From Table 14, public clinics are larger than the private ones in terms of bed capacity and have more staff compliment.

Table 14: Summary Statistics of Variable Inputs for Clinics

Variable	Ownership	Obs	Mean	Std. Dev.	Min	Max
Doctor	Private	8	2	2.62	0	8
	Public	10	1.6	1.35	0	4
Dentists	Private	8	0.25	0.46	0	1
	Public	10	0.1	0.32	0	1
Other Trainees	Private	8	3.5	7.25	0	21
	Public	10	2.5	2.68	0	8
Registered nurses	Private	8	9.34	18.13	0	54
	Public	10	27.8	76.08	0	244
No other Support staff	Private	8	0.13	0.35	0	1
	Public	10	4.5	10.82	0	34
No of Administrators	Private	8	1	0	1	1
	Public	10	0.9	0.32	0	1
Total Licenced beds	Private	8	21.75	16.56	4	50
	Public	10	35.4	70.72	0	234
Consulting room	Private	8	2.38	1.19	1	4
	Public	10	2.3	1.89	0	7

Source: Field survey, (2017)

Output Variables for Clinics

Table 15 below provides a summary of the descriptive statistics on the output variables of both the private clinics and the public ones in the study area. The study reveals that the private clinics had higher outputs in some of the selected output variable such as deliveries, antenatal and postnatal visits. However, the public clinics also produced greater outputs in the outpatient visits, family planning and immunization. The public clinics had an average of 7,218 of outpatient visits which was about 3.14 times more than their private counterparts. However, in terms of the average deliveries, the private clinics exceeded the public ones by an average number of 105. Whiles the public clinics had 1.52 times more for family planning than the private ones, their primary care in terms of output were the same as that of the private. However, there exist variations in the immunization variable, which range from mean number close to 2 for the private to 4 for the public. The private clinics still recorded greater outputs in terms of antenatal and postnatal visits than the public ones. For instance, average total postnatal visits for the public clinics formed only about 29.8% of that of the output for the private ones. Though public clinics produced more outputs in some of the output variables than the private clinics, their measured outputs are however more than proportionate to their relative resource endowment. For example, while public clinics have about 1.6 times and 2.9 times more beds and nurses respectively than the private clinics, their outputs in terms of number of deliveries, antenatal and postnatal visits are substantially lower than that of the private clinics.

Table 15: Summary Statistics of Variable Outputs for Clinics

Variable	Ownership	Obs	Mean	Std. Dev.	Min	Max
Outpatient Visits	Private	8	2301	2791.22	0	8760
	Public	10	7218	8694.20	0	23604
Deliveries	Private	8	433.5	846.57	0	2496
	Public	10	327.6	327.29	0	1092
Family Planning	Private	8	2.5	1.51	1	5
	Public	10	3.8	0.79	3	5
Immunization	Private	8	2.25	1.58	1	5
	Public	10	4	0.82	2	5
Antenatal Visits	Private	8	1528.5	3121.22	0	9168
	Public	10	1305.6	1572.1	0	5412
Postnatal Visits	Private	8	1624.5	3763.66	0	10896
	Public	10	484.80	454.92	0	1212
Primary Care	Private	8	2.5	1.31	1	5
	Public	10	2.5	1.43	1	5

Source: Field survey, (2017)

Table 16 depicts the selected efficiency summary score of private clinics in the study area. According to the Table 16, 4 private clinics had a technical efficiency score of 1, meaning they were at the optimal size for their particular input–output mix. The 4th, 6th and 7th clinics were very close to being efficient whiles only 1 clinic is inefficient. According to Table 16, 2 private clinics had a scale efficiency score of 1. The remaining 6 clinics had scale efficiency scores less than 1 and were thus deemed scale inefficient which indicates a decreasing return to scale.

Table 16: Efficiency Scores of Private clinics

Clinic	Technical Efficiency	crste	vrste	scale	
1	1.00	0.33	1.00	0.33	drs
2	0.73	0.62	0.73	0.86	drs
3	1.00	1.00	1.00	1.00	-
4	0.92	0.54	0.92	0.59	drs
5	1.00	0.95	1.00	0.95	drs
6	0.90	0.79	0.9	0.88	drs
7	0.95	0.82	0.95	0.86	drs
8	1.00	1.00	1.00	1.00	-
Mean	0.94	0.76	0.94	0.81	

Source: Field survey, (2017)

Note: crste = technical efficiency from CRS DEA

vrste = technical efficiency from VRS DEA

Scale = scale efficiency = crste/vrste

According to Table 17, ranking based on technical efficiency scores indicate that 5 public clinics out of 10 have emerged as benchmarking units for the other 5 public clinics. Using the DEA model, out of a total of 10 public clinics, 5 were found to be technically efficient, 3 were very close to being efficient with technical efficiency scores ranging from 0.70 to 0.99 and 2 had technical efficiency scores below 0.50 which makes them inefficient. Also, only 1 public clinic had a scale efficiency score of 1. The remaining 8 public clinics had scale efficiency scores less than 1 and were thus deemed scale inefficient which indicates a decreasing return to scale whiles the 9th public clinic shows increasing return to scale.

Table 17: Efficiency Scores of Public clinics

Clinic	Technical Efficiency	crste	vrste	scale	
1	1.00	0.78	1.00	0.78	drs
2	1.00	0.81	1.00	0.81	drs
3	0.98	0.81	0.98	0.83	drs
4	1.00	1.00	1.00	1.00	-
5	0.73	0.62	0.73	0.86	drs
6	0.44	0.43	0.44	0.97	drs
7	1.00	0.69	1.00	0.69	drs
8	0.4	0.36	0.4	0.9	drs
9	1.00	0.38	1.00	0.38	irs
10	0.92	0.59	0.92	0.64	drs
Mean	0.85	0.65	0.85	0.79	

Source: Field survey, (2017)

Note: crste = technical efficiency from CRS DEA

vrste = technical efficiency from VRS DEA

Scale = scale efficiency = crste/vrste

As depicted on Figure 10, private clinics are efficient than the public ones in the study area. This reflected in DEA model of efficiency.

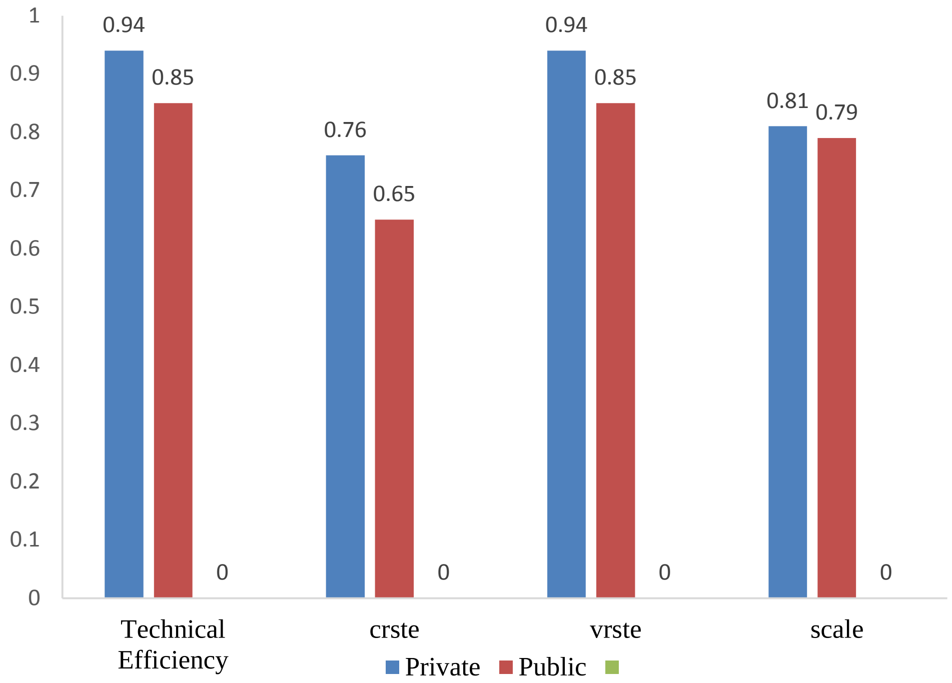

Figure 10: DEA Model for Private and Public Clinics

Source: Field survey, (2017)

Slack Results for Clinics

Input Slack for Clinics

The slack results indicate that 4 of the private clinics were inefficient (Table 18). This implies that these identified private clinics can decrease their input variables in order to help them reach the efficiency frontier, which is the optimal level of efficiency. The magnitude of the excess average input variables was greatly contributed by the 4th private clinic.

Table 18: Input slacks of Private Clinics

Clinic	Clinical Staff	Support Staff	Beds	Consulting Rooms
1	0	0	0	0
2	1.86	0.86	0	0
3	0	0	0	0
4	13	2	4	1
5	0	0	0	0
6	0	0	0.1	0
7	1	0	1	0
8	0	0	0	0
Mean	1.98	0.36	0.64	0.13

Source: Field survey, (2017)

On the other hand, the number of public clinics, which could decrease their inputs to become efficient, was 7 (Table 19). This represents about 70% of the sampled 10 public clinics in the study area. The mean numbers for the excess input variables were as follows: Clinical staff 4.3, Support Staff 0.46, Beds 1.45 and Consulting Rooms 0.51.

Table 19: Input slacks of Public Clinics

Clinic	Clinical Staff	Support Staff	Beds	Consulting Rooms
1	10	0	5	0
2	0	0	0	0
3	4.71	0.71	0	0
4	0	0	0	0
5	1.86	0.86	0	0
6	0	0	0.49	4.14
7	16	0	5	0
8	1.71	0	0	0
9	0	0	0	0
10	7	3	4	1
Mean	4.13	0.46	1.45	0.51

Source: Field survey, (2017)

It was noted that both the private and the public clinics had excess inputs in all the selected input variables. However, the public clinics had greater excess as depicted in Figure 11. In terms of the number of clinics based on ownership, the public clinics had 20% more than the private ones which needed to reduce inputs to attain efficiency. Examining the slack analysis for both ownerships showed that the public clinics have more opportunities for improvement in their input variables in order to attain the optimal level of efficiency (Figure 11).

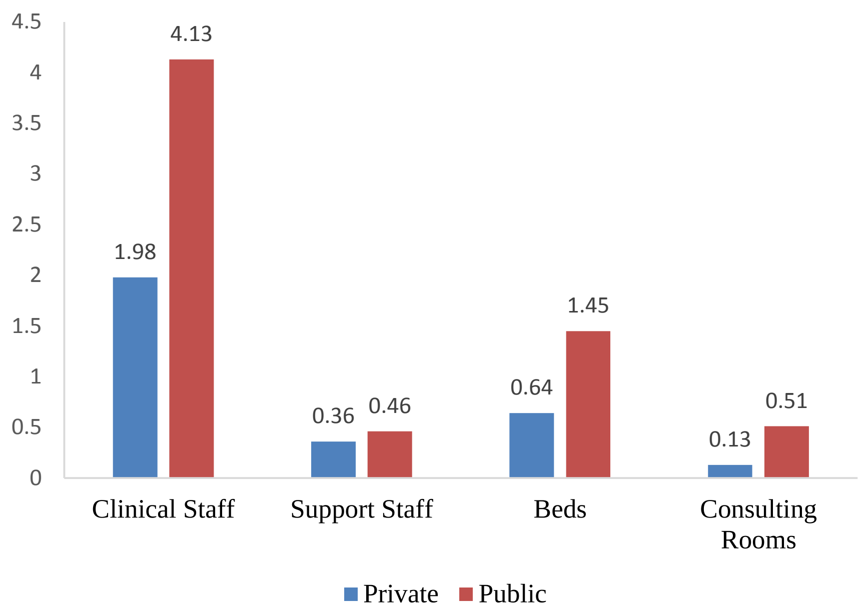

Figure 11: Slack Distribution for Private and Public Clinics

Source: Field survey, (2017)

Output Slack for Clinics

Table 20 shows that the highest output slack observed in outpatient visits is 35,359 for the 4th private clinic followed by 2nd and the 6th in the study area. Regarding the antenatal and postnatal visits it is 0.42 for the 7th private clinic. This implies that, on the average, inefficient private clinics have to increase their outputs number of antenatal and postnatal visits by 0.05 whiles the outpatient visits need to be increased by 6,332.21.

Table 20: Outputs slacks of Private Clinics

Clinic	Antenatal and Postnatal Visits	Outpatient Visits
1	0	0
2	0	9743.64
3	0	0
4	0	35359
5	0	0
6	0	5555
7	0.42	0
8	0	0
Mean	0.05	6332.21

Source: Field survey, (2017)

From Table 21, we conclude that the output slacks show that on average inefficient public clinics have to increase their outputs number of outpatient visits by 15,820.7. It also shows that the output slack of the outpatient visits observed for the public clinics range from 5,560.74 to 40,189.58 in the study area.

Table 21: Outputs slacks of Public Clinics

Clinic	Antenatal and Postnatal Visits	Outpatient Visits
1	0	36234
2	0	0
3	0	20388.7
4	0	0
5	0	9743.64
6	0	5560.74
7	0	40000
8	0	6089.93
9	0	0
10	0	40189.6
Mean	0	15820.7

Source: Field survey, (2017)

In conclusion, it was observed that none of the efficient clinic or hospital had any slack. Slacks exist only for those clinics and hospitals identified as inefficient. However, slacks represent only the leftover portions of inefficiencies; after proportional reductions in inputs or outputs. From the analysis, both the public clinics and hospitals showed that a higher amount of leftover portions in their outputs needed to be used to attain efficiency.

Efficiency Determinants of Clinics

Table 22 gives the determinants of efficiency for the private and public clinics in the study area. From the Table, public ownership and public clinic access were the main variables that significantly affected the technical efficiency of private and public clinics in the region. The analysis further indicate that both operating week and experience of the administrators contributed positively to the technical efficiency level. However, the experience of the administrators had a higher effect than the operating week.

Table 22: Determinants of efficiency of Private and Public Clinics

VARIABLES	Parameter	Coefficient	Standard errors	P-Value
Constant	δ_0	1.023	0.569	0.154
Operating Week	δ_1	0.007	0.086	0.937
Emergency Dept.	δ_2	0.00	0.001	0.819
Public Ownership	δ_3	-0.033	0.146	0.823
Public Clinic Access	δ_4	-0.079	0.161	0.826
Experience of Administrators	δ_5	0.019	0.084	0.245
R^2		0.11		
No. of observations		18		

Source: Field survey, (2017)

Table 23 gives an indication that, the public component of the total selected clinics in the region are less technically efficient as compared with their private counterparts. This is shown by the coefficient value of -0.091.

Table 23: Level of efficiency of Private and Public Clinics

	Coefficient	Standard Error	P-Value
Constant	0.938***	.061	0.000
Public Ownership	-0.091	0.091	0.331
R^2	0.06		
No. of observations	18		

Source: Field survey, (2017)

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

This section presents the summary, conclusions and recommendations of the study. Inherently, it presents some policy recommendations to various policy makers and managers of the health sector in Ghana and in the sub-Saharan Africa. It also presents limitations of the study as well as some suggestions for future research.

Summary

Efficiency signifies a level of performance that describes a process that uses the lowest amount of inputs to produce or create the greatest amount of output without or less waste. The measurement of healthcare efficiency is a difficult exercise for various reasons including the complex nature of the productive process and difficulty in measuring the ideal output of the sector. However, efficiency measurement in healthcare systems represent a first step towards the evaluation of individual performance of production units, which includes hospitals and health centres. One of the popular methods in measuring the efficiency levels of health facilities is the use of Data Envelopment Analysis approach.

The general objective of this study was to compare the technical efficiency of private and public clinics and hospitals in the Central Region of Ghana. Specifically, the study compared the technical efficiency levels, inputs and outputs excess and identified the determinants of technical efficiency of private and public clinics and hospitals in the region. To be able to get supporting efficiency theories and empirical evidence for the study, a good literature review was first conducted. The literature review focused on the various forms of efficiency but puts more emphasis on the different approaches used to measure technical efficiency in the health centres. It as well discussed some studies that have been done on technical efficiency of health facilities in Ghana and other related studies in other parts of the world.

It was noted from the review that most of the studies considered the key inputs and outputs variables for their analysis. Some studies covered multiple years to make effective analysis. It was also noted that these studies reviewed have largely ignored clinics. Furthermore, most of the studies focused on the public healthcare industry.

The study addressed these gaps above to achieve the main objective of the study using DEA model to estimate the technical efficiency levels. It also employed the slack analysis to determine the shortage and excess of input and output variables which needed to be managed to attain efficiency. The study included the clinics which have been largely ignored by a lot of studies. The comparative analysis was based on the ownership type of the health facility in the study area.

Despite the fact that DEA has some pitfalls, it is still the most common method used by scholars. The current study uses the DEA approach to appraise the technical efficiency levels of the selected clinics and hospitals and also run a regression analysis to identify the main factors that influence technical efficiency. The DEA model incorporated four inputs and four outputs. The input variables in the assessment of clinical staff, support staff, licenced beds and consulting rooms. On the other hand, the output variables were antenatal and postnatal visits, outpatient visits, deliveries and family planning.

The total sample of this study comprised clinics and hospitals which are either owned privately or publicly. The whole sample consisted of 34 clinics and hospitals with 18 clinics and 16 hospitals in the study area. The clinics as well as the hospitals were separately analysed based on their ownerships. The 18 clinics in the study area were made up of 8 private and 10 public. On the other hand, the 16 hospitals were composed of 6 private and 10 public.

These obtained data were analysed by using the DEA model to generate the technical efficiency scores, constant return to scale, variable return to scale and the scale efficiency scores to determine the efficiencies of these facilities in the region. Additionally, the input and output slacks for the facilities were analysed to help determine the areas of inefficiencies. The identification of inefficiencies will help managers to identify these sources and adjust accordingly to optimize the healthcare delivery.

The main findings from the study have been highlighted below:

1. Generally, it was noted from the analysis that public clinics are larger than the private ones in terms of bed capacity and have more staff compliment. The mean number as of doctors remains close to 2 for both private and public clinics. The private clinics recorded 1 greater mean number of other trainees than the public clinics. The public clinics in 2016 saw thrice as many registered nurses than the private clinics in the study area. Regarding the number of other support staff

input, the public further recorded more than their private counterparts. There was no variation on the number of administrators for both ownership as they all had close to 1. Whereas the variation in the mean number of licensed beds ranged from 22 in the private clinics to 35 beds in the public clinics, there was no variation for consulting room input for both the private and the public.

2. Again, the study revealed that public hospitals are larger in terms of resource endowment than the private ones. The descriptive statistics from the sample of 16 private and public hospitals in the study area showed some similarities in specific input variables. For instance, there was no significant variation for consulting room input variable for both the private and the public hospitals. On the other hand, there existed some level of variation in the mean input variables between the private and the public hospitals. The average number of doctors remained close to 3 and 4 for private and public hospitals respectively. The public hospitals had 1 dentist as compared to their private counterparts. The private hospitals recorded about 6.4 times greater mean number of other trainees than the public hospitals. The public hospitals in 2016 saw 1.93 times as many registered nurses than the private hospitals in the study area. The variation in the mean number ranges from close to 24 in the private hospitals to 4 in the public hospital. Concerning the number of other support staff input variable, the public hospitals further recorded more than their private counterparts. The analysis showed variation in the mean number of licensed beds which ranged from 47 in the private hospitals to 57 beds in the public hospitals.

3. Moreover, the study revealed that the output produced by the public clinics did not commensurate with their resource endowment. Though the public clinics had about 1.6 times and 2.9 times more beds and nurses respectively than the private clinics, their outputs in terms of deliveries, antenatal and postnatal visits are substantially lower than that of the private clinics. The public clinics had an average of 7,218 of outpatient visits which was about 3.14 times more than their private counterparts. However, in terms of the average deliveries, the private clinics exceeded the public ones by an average number of 105. It was noted that the private clinics had substantial higher outputs in some of the selected output variable such as deliveries, antenatal and postnatal visits. However, the public clinics also produced greater outputs in the outpatient visits but slightly higher in terms of family planning and immunization. Whiles the public clinics had 1.52 times more for family planning than the private ones, their primary care in terms of output were the same as that of the private. However, there existed variation in the immunization variable which ranged from an average number close to 2 for the private to 4 for the public. The private clinics still recorded greater outputs in terms of antenatal and postnatal visits than the public ones. For instance, average total postnatal visits for the public clinics formed only about 29.8% of that of the output for the private ones.
4. The study revealed that public hospitals manifested higher outputs in all the selected variables than the private ones in the region. The public hospitals had about 4.16 times more average number of outpatient

visits than the private hospitals. Similarly, public hospitals recorded about 3.6 times and 1.41 times more in average number of deliveries and family planning respectively. Furthermore, both the antenatal and postnatal visits for the public hospitals were substantially greater than the private ones.

5. The private clinics were found to have the highest mean technical efficiency, CRS, VRS and scale efficiency scores than the public ones in the region. The study revealed that the private clinics had average technical efficiency score of 0.94 as against 0.85 for the public ones in their input-output variable mix for production. The private clinics further displayed a higher average constant returns to scale (CRS) of 0.76 than the public ones with 0.65 which implied that most of the private clinics were operating at their most productive scale size. However, both ownerships exhibited higher levels of decreasing return to scale for their facilities. This implies that a percentage increase in input variables of these clinics will result in less than proportionate increase in their output variables.
6. Again, in most of the ranking indicators, DEA model revealed that the public hospitals were more technically efficient than their private counterparts. The public hospitals exhibited 80% of their units having technical efficiency score of 1 as compared with 50% for the private hospitals. This was further confirmed by the 67% of the private hospitals found to be operating at the decreasing return to scale.
7. The study revealed that the public clinics had greater excess of input variables than the private ones. From this study, the public clinics had

about 20% more of input wastage than the private ones which needed to be reduced to attain efficiency. It was noted from the slack analysis that both ownership types have opportunities for improvement in input variables but comparatively, the public clinics have more capacity for improvement to attain optimal level of efficiency.

8. It was further noted from the study that the public hospitals had excess inputs in all the selected input variables as compared with their private counterparts. In terms of the extent, the private hospitals had about 16.6%, which needed to reduce inputs to attain efficiency as against 50% for the public ones.
9. In terms of the output deficiency, the public clinics and the public hospitals exhibited greater amount of output slacks that had to be increased. Averagely, the analysis indicated that the public clinics had to increase their output on outpatient visits by 15,820 as compared with 6,332 for the private ones. Similarly, the public hospitals had 4 units needed to augment their antenatal and postnatal visits. In terms of outpatient visits, the public hospital which needed to increase its output by 3,766 to be efficient.
10. The coefficient results of the regression analysis identified operating week and the experience of administrators as other variables which positively influenced the technical efficiency levels of both private and public clinics in the region. However, public ownership and public clinic access inversely influenced their technical efficiency levels. Moreover, public ownership and the experience of administrators were identified as variables which positively influenced the technical

efficiency levels both private and public hospitals. Contrary, operating week and public hospital access affected their efficiency levels.

Conclusions

Given the findings of this study, the following conclusions were drawn:

1. Private clinics were more technically efficient than the public clinics in the study area. However, in terms of the hospital, the public hospitals were more technically efficient than the private hospitals. This study is in line with Hollingsworth (2003) in his meta-analysis of 317 publications, which concludes that public provision of healthcare services may be potentially more efficient than private. It is further supported by Jehu-Appiah et al. (2014) in their analysis of ownership and technical efficiency of hospitals and concluded that private hospitals exhibited the highest level of inefficiency compared to public health facilities.
2. In addition to the above, the public clinics had greater excess of input variables than the private ones. The public clinics had close to 20% more of input wastage than the private ones, which needed to be reduced to attain optimal efficiency, level. Similarly, the public hospitals exhibited excess inputs in all the selected variables as compared with their private counterparts.
3. In the case of output variables, both the public clinics and hospitals exhibited greater amount of excess that have to be increased to attain a higher level of efficiency.

4. Finally, operating week and the experience of administrators were identified as determinants, which positively influenced the technical efficiency levels of both the private and the public clinics. However, public ownership and experience of administrators were the main determinants which positively influenced the level of technical efficiency in the private and public hospitals.

Recommendations

Based on the findings of the study, the following policy recommendations were made:

1. A reasonably pragmatic suggestion is that private and public clinics and hospitals efficiency should be monitored by managers using DEA method on an annual basis, which will help clinics and hospitals that steadily become inefficient to take urgent action in order to correct and improve their efficiency.
2. As stated by WHO, clinics are usually supposed to be run for about 4 to 5 hours a day and patients are expected to leave after treatment without staying all night. However, this was not the case from the study. Hence policy makers and management should ensure that clinics conform to these international standards and patient are transferred to the hospitals where they would be admitted for treatment of various diseases.
3. Managers and policy makers should identify the areas of inefficiencies in both inputs and outputs for effective reallocation of resources to increase the level of technical efficiency. As shown by the slack

analysis, the public clinics and hospitals had excess resources, which were not utilized. It, therefore, suggests that the excess input found in the public can be transferred to clinics and hospitals that lack them. Managers of public clinics and hospitals can convert excess beds and consulting rooms to occupy outpatient's secondary prevention services.

4. Finally, there is a need to break down into a manageable size both clinics and hospitals identified with technical inefficiencies related to large size (decreasing returns to scale) there is a need to break down such clinics and hospitals into a manageable size.
5. There is the need to build the capacity of the private sector to manage resources and ensure basic standards are met to attain high level of efficiency.
6. Private and public clinics and hospitals should employ experienced administrators so as to enhance their technical efficiency.

Limitation of the Study

Firstly, some clinics and hospitals could not provide the needed and adequate data for the analysis, therefore they were excluded whiles others found it difficult to disclose the information.

Secondly, due to the lack of data, this study did not include the cost of expenditures on inputs. In addition, the quality of labour within the same health workforce category was not included. This may vary depending on individual health worker skills, professional experience and health status.

Third, it was not possible to adjust for the quality of both outputs (e.g. successful outpatient visits and inpatient admissions in terms of full recovery from illness, severity of disease differences) and inputs (e.g. more skilful and hardworking clinical and support staff). Therefore, it may be argued that there may exist variation in the quality of healthcare delivered by different private and public clinics and hospitals in the region.

Areas for Further Research

This study covered private and public clinics and hospitals in the Central Region of Ghana only. Hence, there is the need to widen the scope to cover all private and public clinics and hospitals in Ghana. Though the present study looked at technical efficiency, a study on allocative efficiency would probably give more insight into efficiency studies. It would also be interesting to look at technical efficiency and allocative efficiency using data from other private and public clinics and hospitals in Ghana to evaluate technical efficiency among the regions.

DEA model does not rank the efficient clinics and hospitals, but only identifies them as 100% efficient, which means that additional information would be required to enable comparisons between efficient clinics and hospitals. Therefore, the "super efficiency" approach by Andersen & Petersen (1993), which is a statistical method for ranking DMUs in the DEA literature, could be adopted for future research.

Regarding methodological extensions, it is feasible to compare the results of the DEA model in the present study with those results obtained from other alternative techniques, such as stochastic frontier analysis (SFA). In fact, the use of SFA could yield a different set of efficient data, which might or might not be in agreement with the DEA results from the current study.

Hence, this investigation would be helpful to confirm whether analytical methods other than DEA could offer any additional value to the available information on the efficiency results that DEA provides.

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APENDICES

Appendix A – Questionnaire

UNIVERSITY OF CAPE COAST
COLLEGE OF HUMANITIES AND LEGAL STUDIES
FACULTY OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

QUESTIONNAIRE FOR PRIVATE AND PUBLIC CLINICS IN THE CENTRAL REGION OF GHANA

Dear Sir/Madam,

This questionnaire is aimed at data collection on Technical Efficiency of private and public Clinics in the Central Region of Ghana. It is aimed at carrying out research work in partial fulfilment of the requirements for the award of Master of Philosophy in Economics.

Please, kindly complete this questionnaire as honesty and carefully as you can and be assured that information provided will solely be used for the research.

Thank you for your co-operation.

A) Background:

1. What is the ownership type of this clinic and hospital? Private [ ] Public [ ]
2. Gender of the administrator male[ ] female [ ]
3. How long had he/she worked as an administrator? less than 10years[ ] 10-20 years[ ] 21-30 years [ ] above 30years [ ]
4. Educational level of the administrator? Basic [ ] Secondary [ ] Tertiary [ ] Professional[ ]
5. Is this a critical access clinic? Yes [ ] No [ ]

6. Reporting Period used (beginning and ending date)

__ __ / __ __ /__ __ __ __ to __ __ / __ __ /__ __ __ __

Month Day Year Month Day Year

7. Number of days operating in a week____________________

B) **Input variables**

Report full-time (40 hours or more) and part-time (less than 40 hours) personnel who were on the hospital/facility payroll at the end of your reporting period. Exclude private-duty nurses, volunteers, and all personnel whose salary is financed entirely by outside research grants. Exclude physicians and dentists who are paid on a fee basis.

For each occupational category, please report the number of staff vacancies as of the last day of your reporting period. A vacancy is defined as a budgeted staff position which is unfilled as of the last day of the reporting period and for which the hospital is actively seeking either a full-time or part-time permanent replacement. Personnel who work in more than one area should be included only in the category of their primary responsibility and should be counted only once.

8.

		Total Full-Time (40 hr/wk or more)	**Total Part-Time (Less than 40hr/wk)**	**Vacancies**
a)	Doctor			
b)	Dentists			
c)	Other trainees			

d)	Registered nurses			
e)	Licensed practical (vocational) nurses			
f)	Midwife			
g)	Laboratory Technician			
h)	Pharmacist			
i)	Community health officers			
j)	Health education officers			
k)	Others[specify]____ __________________			

9. Number of support staff

		Total Number
a)	Administrator	
b)	Environmental Health Officer	
c)	Others[specify]________________________	

10. .Beds set up for staff use on night duties at the end of the reporting period ____________________

11. Total licensed beds ____________________

12. Emergency department visits ____________________

13. What is the total number of inpatients past year ____________________

14. What is the total number of outpatients (past year ____________________

15. Please indicate the number of consulting rooms available__________________

C) Output factors

16. Indicate the category that BEST describes the clinic or the type of service it provides to the MAJORITY of patients:

		Not Available	Low	Moderate	Moderately High	High
a)	General consultations	☐	☐	☐	☐	☐
b)	Mother and Child Health	☐	☐	☐	☐	☐
c)	Vaccinations	☐	☐	☐	☐	☐
d)	Deliveries	☐	☐	☐	☐	☐
e)	Family Planning	☐	☐	☐	☐	☐
f)	Information and Education for health	☐	☐	☐	☐	☐
g)	Laboratory services	☐	☐	☐	☐	☐
h)	Tuberculosis and other respiratory diseases	☐	☐	☐	☐	☐
i)	Chronic diseases	☐	☐	☐	☐	☐
j)	Community health education	☐	☐	☐	☐	☐
k)	Home health services	☐	☐	☐	☐	☐
l)	Hospital-based outpatient care centre services	☐	☐	☐	☐	☐
m)	Immunization programme	☐	☐	☐	☐	☐
n)	Indigent care clinic	☐	☐	☐	☐	☐
o)	Primary care department	☐	☐	☐	☐	☐

p)	Rural health clinic	☐	☐	☐	☐	☐
q)	Social work services	☐	☐	☐	☐	☐
r)	Teen outreach services	☐	☐	☐	☐	☐
s)	Transportation to health services	☐	☐	☐	☐	☐
t)	Volunteer services department	☐	☐	☐	☐	☐
u)	Other services	☐	☐	☐	☐	☐

17. Please indicate the following output variables per month

		Total Number
a)	Number of deliveries	
b)	Number of out-patient visits	
c)	Number of antenatal	
d)	Number of postnatal	

Appendix B – Introductory Letter

UNIVERSITY OF CAPE COAST
COLLEGE OF HUMANITIES AND LEGAL STUDIES
FACULTY OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

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8th February, 2017

INTRODUCTORY LETTER
(MS. HILDA SERWAA OBENG)

Dear Sir/Madam

I wish to introduce **Ms. Hilda Serwaa Obeng** a graduate student of the Department of Economics, University of Cape Coast, who is researching on the topic **"Comparative Study of Technical Efficiency of Private and Public Clinics in the Central Region of Ghana".**

We would be grateful if the student is given the necessary assistance for the completion execution of her project work.

We wish to assure you that the information provided would be treated with utmost confidentially.

Thank you.

Yours faithfully,

Emmanuel E. Asmah (Ph.D)
[Head]