

Efficiency and Productivity Growth in the Health Care Systems of Ghana: Regional Comparison Analysis using DEA

SAMUEL AMPONSAH

Institute for International Strategy
Tokyo International University
samponsa@tiu.ac.jp

SMART EDWARD AMANFO

Graduate School of Economics
Tokyo International University
smart6783@gmail.com

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Abstract

Based on thirteen years of regional health care systems data, this paper analyzes efficiency and productivity growth of Ghana's regional health care systems using the ten administrative regional data sets on institutional maternal mortality ratio. The aim is to assess how each region had succeeded in reducing maternal deaths in relation to the Millennium Development Goals (MDGs) 4 and 5 and recent health care policy reforms. Data Envelopment Analysis (DEA) was used to estimate the relative efficiency scores and DEA based-Malmquists Productivity Index (MPI) was used to calculate Total Factor Productivity Growth (TFPG) and sources of growth. Our results indicate that on average there was efficiency improvement index of about 12.26%, technological improvement index of about 28.3% and Malmquist productivity index of 36.39%. The main source of productivity growth as per the components of the DEA-Banker, Charnes, and Cooper (BCC) Malmquist productivity growth index was as result of frontier-shift (innovation). From our DEA-tobit results, both total fertility rate and insurnace are found to be negatively related to Malmquist productivity growth index.

Keywords: Ghana, Productivity Growth, Regional Health Care Systems, DEA, Comparative Analysis

1. INTRODUCTION

During the Structural Adjustment Programmes (SAPs) in the 1980s, the health care systems in Ghana witnessed a drastic reduction in terms of investment despite the Alma-Ata Declaration in 1978¹. That fractiously led to regional inequality in health services production and its attendance problems such as maternal mortality rates, infant mortality rates and malnutrition [47]. Recognizing the critical impact of population health on the overall socio-economic advancement, especially under the endogenous growth theory the World Health Organization (WHO) established the Commission on Macroeconomics and Health that studies the links between increased investment in health, economic development and poverty reduction [1]. One of the revelations of the study was that ill-health contributes significantly to poverty and low economic growth [2]. In line with the MDGs 4 and 5,² the Heads of State of African countries made a commitment to allocate at least 15% of their annual national budget to improve the health sector [3].

As a signatory to the MDGs and Abuja Declaration, Ghana responded by introducing a number of health systems reforms. These include, among others, the Health Service Community-Based Health Planning and Services (CHPS) policy in 2003, National Health Insurance Scheme (NHIS) in 2004, expansions in health and health care infrastructure across the ten administrative regions, and increased in the admission intakes of health related professional training institutions. In particular, the NHIS was intended to make health care accessible to the poor and vulnerable group of people and the political will to cause the extinction of the existing "Cash and Carry System"³. The Delivery Care Free policy was aimed at reducing the prevailing high records of maternal mortality ratios with variant degree across the health systems in urban, rural and the ten regions of the country.

In spite of the above state social interventions and public health production policies, the available macro data points indicate that, the health sector in Ghana is performing below average in terms of funding when compared with government commitments made during the various health declarations. For example, government needed to spend at least \$US86 per person in order to provide basic health services. In 2013, the government of Ghana only spent \$US63 on each person's health [8]. In the years 2009-2012, less than 30% of the approved funds for health were actually received by the health sector. It is estimated that, by the year 2010 50% of the District Health Directorates (DHDs) did not receive funds from government or assembly level to provide maternal

¹The Declaration of Alma-Ata was adopted at the International Conference on Primary Health Care Primary Health Care (PHC) Almaty in 1978

²The MDG 4 was to reduce infant mortality and goal 5 was to promote maternal health

³Cash and Carry System refers to a situation in which the health need of an individual Ghanaian was only attended to after initial payment for the service was made

healthcare [8, 7]. As a result of the government inability to spend adequately due to limited fiscal space emanating from poor macro economic performance, the burden of paying for health falls heavily on households [8, 7, 9].

Despite the NHIS aiming to achieve universal health insurance coverage in Ghana, 36% of all health spending in the country was spent by households upfront, without insurance in 2013 [8, 7, 9, 10]. Apart from financing, inequitable distribution of human quality resources is also a daunting challenge facing the regional health settings. According to the recent statistics, Ghana has 0.10 physicians per 1,000 population compared to the WHO standard of 0.20 physicians per 1,000 population. The nurse population is 1.14 nurses per 1,000 population compared to the WHO standard of 2.20 per 1,000 population. The distribution of staff is skewed towards the urban areas. Approximately 50% of the health workforce is located at the district level, while 16% is located at the sub district level. The regional hospitals take up 9% of the workforce and a further 12% is located within the teaching hospitals. In 2012, the poorest staffed region with respect to nurses was the Northern Region with one nurse for every 1,601 population compared to the national average of one nurse to 1,251 population according to the Health Sector Medium Term Development Plan [6].

The aforementioned illustrations indicate characteristically, the extent to which the national and for that matter the regional health care systems in Ghana are constrained in terms of financing, logistics and personnel. However, with the growing health care needs in the face of limited health production inputs across the globe, specifically in the developing and low middle income countries like Ghana, attention of policy makers must be geared toward efficiency and productivity growth in the sector. WHO, [4] indicates that, spending money more efficiently and equitably will increase health coverage, increase financial protection and improve health outcomes (World Health Organisation, 2015). It is estimated that, between 20 to 40% of health spending is wasted, depriving many people of badly needed care [4, 5]. Thus, ensuring efficiency and total productivity growth (TFPG) in the health care systems will be the trajectories on which the opportunity of optimizing the usage of limited health inputs could be achieved. Productivity growth provides society with an opportunity to increase the welfare of people (Anders, 2007) . Efficiency of production refers to the ability of a health system's Decision Making Units (DMUs)⁴ to generate the maximum health services outputs from a given set of inputs [36]. In the case of health systems, productivity and efficiency analysis are proxy tools that could be used to determine whether service purchasers are getting value for money. There are different types efficiency estimates. However, in our study, the term *efficiency* will denotationally mean technical and technological efficiencies.

The main goals of the paper are as follow: First, to rigorously study the

⁴DMUs is used here to refer to health care decision makers

evolution of efficiency change in the health care systems across the ten administrative regions of Ghana in line with major policy reforms over time period. Second, to analyze the trends and sources of productivity growth in the same health care systems over a period of 13 years by applying Data Envelopment Analysis (DEA), and TFPG using Malmquits Productivity Index (MPI). To the best of our knowledge, no such empirical work that examines efficiency and productivity growth in the regional health care system exists in Ghana. The outcomes of this current study could therefore provide scientific information for all relevant actors in formulation and implementation of health policies regarding performance in the health sector.

The structure of the rest of the paper is as follows. Section 2 gives a concise overview of the national and regional health care systems in Ghana; Section 3 examines the existing relevant literature on health care efficiency and productivity growth; Section 4 outlines the model for the efficiency estimates; Section 5 provides the data and methodology for the DEA; Section 6 presents the results and discussions; Conclusions, limitations and policy implications of the study are provided in Section 7.

2. THE REGIONAL HEALTH CARE SYSTEM DURING RECENT REFORM

As a constitutional requirement, Act 525 of 1996 mandated the Ghana Health Service (GHS) to provide and prudently manage comprehensive and accessible health service with special emphasis on primary health care at regional, district and sub-district levels in accordance with approved national policies. As a results of its mandate, decentralization and health sector reform, services are integrated as one goes down the hierarchy of health structure from the national to the sub-district.

According to the GHS, at the regional level, curative services are delivered at the regional hospitals and public health services by the District Health Management Team (DHMT) as well as the Public Health division of the regional hospital. The Regional Health Administration or Directorate (RHA) provides supervision and management support to the districts and sub-districts within each region.

Also the GHS has indicated that at the district level, curative services are provided by district hospitals many of which are mission or faith based. In addition, public health services are provided by the DHMT and the Public Health unit of the district hospitals. The District Health Administration (DHA) provides supervision and management support to their sub-districts.

In contrast, at the sub-district level both preventive and curative services are provided by the health centers as well as out-reach services to the communities within their catchment areas. With the introduction of CHPS in 2003, basic preventive and curative services for minor ailments are usually addressed at

the community and household level.

Although the **GHS** is mandated to provide and prudently manage comprehensive and accessible health service in Ghana, it is the National Health Insurance Authority (**NHIA**) that finance health care in Ghana using the **NHIS**. The **NHIS** was implemented in 2005 and aims to attain universal health insurance coverage in relation to persons resident in the country, persons not resident in the country but who are on visit to Ghana, and to provide access to healthcare services to persons covered by the Scheme.

Healthcare services in the country has seen tremendous improvements. For example, the **GHS** 2014 annual report indicates that outpatients' (**OPD**) attendance has increased subsequent to the rollout of the **NHIS** nationwide. In 2014, the total **OPD** attendance comprised 83.5% insured and less than 17% being out-of-pocket (**OOP**) clients. This proportion of **OPD** attendance that was insured is almost same as what was recorded for 2013. What is interesting is that out of the total **OPD** attendance 62.7% were females.⁵

Apart from the **NHIS**, another factor driving the high level of **OPD** attendance in Ghana is the **CHPS** zone policy. According to the **GHS** 2014 Annual Report, **CHPS** contributed about 10% of the total service delivery in the country. And this has been possible because the number of **CHPS** zones have also increased over the years. For instance, the number of **CHPS** zones have increased from zero in 2000 to 2,948 in 2014.

According to the report, all regions in Ghana recorded slight increases in the number of medical officers except Central and Brong-Ahafo regions where many medical officers were upgraded to specialists. These increases in the number of medical officers have contributed to improvements in doctor to population ratio. By considering the 2014 indicators from the report, we can see marginal improvement in the doctor population ratio from 1:10,000 in 2013 to 1:9043 in 2014. Although many regions observed improvement in doctor to population ratio but the issues of inequity in doctor distribution continues to linger. Similar to the doctor population ratio, there are high-regional variations in professional nurses serving in the various health facilities across the country. **GHS** 2014 Annual Report, shows that the North region has only 22% of its nurses being professionals, while the Greater Accra region is the only region that meets the norm of 60% professional nurses to 40% auxiliary nurses.

3. REVIEW OF RELATED LITERATURE

The available literature on health care productivity and efficiency analysis is quite limited compared to other sectors of an economy. This is due to, in part, the complexities associated with measuring health outcomes and unavailability of

⁵In terms of actual figures, **OPD** attendance for 2012, 2013, and 2014 are 29,565,620, 30,160,028, and 31,105,432 respectively.

price information. Historically, the first application of **DEA** in health care began with H. David Sherman's doctoral dissertation in 1981 [21, chap. 16]. (Cooper W. et al 2011) . As there has been a growing demand for accountability in relation to how health care resources are optimally allocated and international concerns about efficiency of health care systems, the literature on the subject matter is also soaring over the few decades. Previous empirical health care productivity measurements have been conducted at both micro, macro and international levels comparing and ranking DMUs. Medeiros et al. [42] in their study, estimate relative efficiency of health care systems across all EU countries using macro data set. Afonso and Miguel [11], applied two non-parametric approaches namely the Free Disposable Hull (**FDH**), and **DEA** to education and health expenditure efficiency in OECD countries. In an attempt to measure the impact of corruption and quality of institutions on the efficiency of public health expenditure, Novignon [46] empirically estimate efficiency of public health expenditure in Sub-Sahara Africa. He found out that, corruption and poor public sector reduce health expenditure efficiency. Mirmirani et al. [45] used **DEA** to study health care efficiency in Transition Economics and found that, the most efficient health care systems were OECD countries. Pinar and Thuy [26] studied the effects of changes in public policy on efficiency and productivity of general hospitals Vietnam employing **DEA** methodology. Their study found evidence of improvement in the productivity of Vietnamese hospitals with progress in total factor productivity of 1.4%. A study conducted by Honjo and Verhoeven [25] titled *The Efficiency of Government Expenditure: Experiences from Africa* assess the efficiency of government expenditure on health and education in 38 countries in Africa in 1984-95 and compared them with countries in Asia and Western Hemisphere. The results revealed that, on average, countries in Asia and Western Hemisphere were efficient than Africa countries. Their results further suggested that, improvement in educational attainment and health output in Africa countries required more than just higher budgetary allocation. Amado and Sergio [13] empirically assessed the performance of 337 primary health centres in Portugal in 2009. The outputs employed were family planning consultations; maternity consultations; consultation by patient grouped by age intervals 0-18; 19-64; and 64 plus; home doctor consultations; home nurse consultations; curatives and other nurse treatments; injections delivered by a nurse; and vaccination given by a nurse. And the inputs considered were the number of nurses; number of doctors; and administrative and other staff. They found a frontier technical efficiency score of 84%

The **DEA** methodology had hardly appealed to statisticians and econometricians because of its deterministic nature which makes its application prone to outliers. To correct this deficiency, many gurus in **DEA** methodology adjust for the so-called environmental factors. Environmental variables describe factors which could influence the efficiency of a DMU, but are not traditional inputs to the production process and assumed outside the control of the

manager [30, see chap. 5]. Thus, the DEA methodology follows a multistage analysis. The first-stage involves measuring the relative efficiency scores through the DEA and the second-stage is carried out to assess the plausible predicates of efficiency using regression analysis. In their study tagged *Two-stage hospital efficiency analysis including qualitative evidence: A Greek case*, Xenos et al [57] applied Tobit regression model to measure contextual factors that impact on the efficiency scores of 112 Greek public hospitals. They included environmental factors viz: Occupancy Rate and the ratio between outpatient Visits and Inpatient Days. Their conclusion was that the inclusion of Risk-Adjustment Mortality Rate, significantly influenced the hospitals efficiency at p-value-0.05. Lionel [40] in his study tagged *Determinants of Health Spending Efficiency: a Tobit Panel Data Approach Based DEA Efficiency Scores*, assessed the determinants of health expenditure efficiency using 150 countries data from 2005 to 2011. He applied a Tobit Panel Data based on DEA Efficiency Scores and concludes that, Carbon dioxide emission, gross domestic product per capita, improvement in corruption, the age composition of the population, population density and government effectiveness were significant determinants of health expenditure efficiency.

Given the dynamics in both demand and supply sides of the health care market, monitoring the performance of in the health care environment over time is inevitable. There are often policy changes, epidemiological transition, new regulations, new medical technologies and adaptation of new organizational structure that affect the performance of organizations over time Yasar et al. [49]. Measuring the performance of the health care systems over time gives the opportunity to measure efficiency change, technical efficiency change, technological progress which captures total factor productivity growth. It has been argued that, sometimes a 1-year time lag may not be enough to see impact of important policy, technological innovations, and other organizational changes that impact the health care delivery organizations⁶. Sorin [16] study technical efficiency and productivity growth in the Central and Eastern European health systems. He employed an output orientation DEA to measure the technical efficiency in the health care systems using data on infant death and life expectancy as health outputs for the period 1999 to 2009 in the first stage of his analysis. In the second stage, the study used Malmquist Total Factor Productivity Index based on data envelopment analysis to assess the productivity change over the time period for each country. His results suggested that, technical efficiency varied across new EU member state and that translated into potential savings. The inter-connection between total factor productivity growth and population health had been researched over the few decades. According Anders [29], health influences TFP growth directly through household income and wealth, and indirectly through labour productivity,

⁶see eg; Yasar A. Ozcan Chap. 6

savings and investments and demography, by reducing various forms of capital and technology adoption. Anders further argues that, healthy workers are more productive, all else being equal, and that, with lower mortality rates, the incentives to save increases and leads to higher TFP.

What is obvious from the previous studies are that, majority of them were carried out in developed world such EU and OECD member states with little focus on developing regions like Ghana where higher improvements are needed. Kirigia [36, 37] however, envisaged that over the next two decades Africa shall witness a revolutionary growth in studies involving the application of tools such as **DEA** in productivity and efficiency analysis monitoring.

4.0 METHODOLOGY

4.1 **DEA** Model

There are five major classes of methods in which comparative performance evaluation could be carried out namely: Ratio Analysis, Least-Squares Regression (LSR), Total Factor Productivity (TFP), Stochastic Frontier Analysis (SFA) and **DEA**⁷. Each of these methods by theoretical categorizations, fall under either parametric or non-parametric technique with their unique strengths and weaknesses. Motivated by the force of relative scarcity of resources, a central problem for all economic agents, the main objective of carrying out productivity and efficiency analysis is to evaluate the performance of firms, public organizations, or more generally DMUs that convert inputs into outputs Tarja and Pekka [34]. Unlike the traditional linear programming which is *ex ante tool* in planning, the **DEA**-based linear programming is employed as *ex post tool* to evaluate the performance that has already been observed⁸. In order to estimate the relative technical efficiency and productivity growth of the regional health care systems from the ten administrative regions of Ghana, an output-orientation **DEA** and a **DEA**-based **MPI** have been used in this current paper.

The conceptual innovation of **DEA** as a productivity and efficiency measurement tool is credited to the work of Farrell in 1957. However, its popularity as a practical research tool is grounded on the efforts of Charnes, Cooper and Rhodes in 1978 and further expanded by Banker, Charnes and Cooper in 1984 [27, see eg. Hollingsworth et al 2008]. Despite the documentation of its limitations, **DEA** applications in productivity and efficiency analysis has received attention by researchers and policy makers in⁹ in the various sectors of economy such as airlines, agriculture, health sector,

⁷See Yasar A. Ozcan, 2014, pp 3-12 for details information

⁸see Tarja and Pekka (2015, pp. 175)

⁹See Jacobs and Peter, 2006 for detail information the strenghts and limitations of **DEA** in the context of health care production

bank branches, schools and so on. **DEA** methodology has been widely employed in assessing the health care production productivity and efficiency at the micro level (eg. district and municipal hospitals) and at the macro level (eg. cross-country health care systems performance analysis).

DEA uses a linear non-parametric method to measure the relative efficiency of homogeneous decision making units platforms. **DEA** measures efficiency in two stages. In the first stage, a frontier is identified based on either a given homogeneous health care systems employing the least input mix to produce health output or those achieving the maximum output mix given their input based on either input or output orientation. In the second stage, each health care DMU under investigation is assigned an efficiency score by comparing its output/input ratio to that of efficient DMU(s) that operating on the theoretical production frontier Jacobs et al. [31].

For a **DEA** empirical analysis, the flexibility of the model provides opportunity to determine the input weight u_i and output weight v_j that maximizes efficiency score of a given DMU. In general theoretical argument, a DMU is said to be "efficient" if it obtains from the **DEA** model an estimated relative efficiency score of 1. Otherwise, the DMU is classified as inefficient. By extension, a health care system is efficient if it is able to maximize its objectives in the face of limited resources. Smith et al. [55] opined that, the objectives of a health care system could be summarized in those limited number of heading such as: the health conferred on the citizenry by the health system, responsiveness to individual needs and preferences of the patients, financial protection offered by the health system and productivity of utilization of health resources.

The most frequently used models in **DEA** are Charnes, Cooper, and Rhodes (**CCR**) and Banker, Charnes, and Cooper (**BCC**) named after Charnes, Cooper and Rhodes; and Banker, Charnes and Cooper respectively. **CCR** was developed in 1978 and assumed input orientation and proposed that the production technology exhibits a constant returns to scale (CRS). On the other hand, the **BCC** model was inverted in the year 1984. Propounders of the **BCC** model contrary to the **CCR** model assumed a variable returns to scale (VRS). Both models carried and expanded on the concept of "technical efficiency" theorized by Farrell in 1957. In generic term, Farrell [23](1957) defined technical efficiency as *the ability of a firm to obtain maximum feasible output from a given amount of inputs*. Kirigia [36, 37, 38] defined technical efficiency contextually as a "scenario in which a health-related DMU produces optimal/maximum output from the available health service inputs". Ozcan [48] also opined that "an organization is technically efficient if it uses the minimum combination of resources to produce a given quantity or level of care." A DMU is rated technically efficient if it lies on the empirically estimated efficient frontier. DMUs that lie below the efficiency frontier are otherwise considered as technically inefficient.

Ramanathan [50] formulated fractional **DEA** mathematical programmes based on **CCR** assumption as follows: Let there be N DMUs whose efficiency have to be compared. One hypothetical DMU is assumed; eg. the m th DMU, (one regional health care system in our case) and maximize its efficiency. The m th DMU is technically referred to as the reference DMU. The mathematical programme is therefore shown as:

$$\text{Max} E_m = \frac{\sum_{j=1}^J v_{jm} y_{jm}}{\sum_{i=1}^I u_{im} x_{im}} \quad (1)$$

subject to

$$0 \leq \frac{\sum_{j=1}^J v_{jm} y_{jn}}{\sum_{i=1}^I u_{im} x_{in}} \leq 1; \quad n = 1, 2, K, N$$

$$v_{jm}, u_{im} \geq 0; i = 1, 2, K, I; \quad j = 1, 2, K, J$$

where E_m is the efficiency of the m th DMU,
 y_{jm} is j th output of the m th DMU,
 v_{jm} is the weight of that output,
 x_{im} is i th input of the m th DMU,
 u_{im} is the weight of that input, and
 y_{jn} and x_{in} are j th output and i th input, respectively of the n th DMU, $1, 2, \dots, N$.
It should be noted that n includes m .

With particluar reference to the Ghanaian health care systems constraints, we belief that the application of variable returns to scale is more suitable in carrying out our research. The variable returns to scale model also known as the **BCC-DEA** is an important extension of the **CCR-DEA** by Banker, Charnes, and Cooper (1984) which is the generalization of the original **DEA** model for technologies exhibiting increasing, constant, or diminishing returns to scale at different points on the production frontier [52, 53, adopted from Subhashi pp. 46]. For the purpose this paper, 1 is modified to capture **BCC-DEA** empirical technical efficiency frontier under the **BCC-DEA** (Variable Returns to Scale) assumption. **DEA** estimates the techical efficiency Technical Efficeincy (**TE**) of a health care-related DMU compared with number of health care systems in a peer-wise group as suggested by Charnes et al. [18] as follows:

$$MaxTE_k = \sum_{r=1}^s u_r y_{rjk} + u_k \quad (2)$$

subject to

$$\begin{aligned} \sum_{i=1}^m v_i x_{ijk} &= 1 \\ \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} + u_k &\geq 0; \quad j = 1, 2, \dots, n \\ u_r &\geq 0; r = 1, 2, \dots, s, \quad i = 1, m \end{aligned}$$

where

y_{rj} ($r = 1, 2, \dots, s$) = The quantity of r^{th} health system's outcome observed for j^{th} healthcare-related-DMU

x_{ij} ($i = 1, 2, \dots, m$) = the quantity of r^{th} health system's input demand observed for j^{th} healthcare-related-DMU

v_i = Weight assigned to a given input i

u_r = Weight assigned to a given output r (health outcome)

n = Number of DMUs (ten regional health care systems in our case)

k = the health care system being assessed in the set of

$j = 1, 2, \dots, n$ systems.

Technical efficiency can be calculated from either the perspective of input-orientation or output-orientation. Input-oriented technical efficiency measures keep output fixed and explore the proportional reduction in input usage which is possible, while output-oriented technical efficiency measures keep input constant and explore the proportional expansion in output quantities that are possible according to Jacobs [31, 32]. The decision to adopt either an input-orientation or an output-orientation **TE** measurement is a goal driving principle. If the goal is to assessing how health resources are minimally combined to produce a given level of health output, then the input-orientation is more desirable. Otherwise output-orientation is would has to be considered.

We employed an output-orientation **BCC-DEA** model in our paper. The choice of output-orientation is based on the assumption that within the context of the National Development goals, the health sector in Ghana seeks to improve the overall health status of Ghanaians by reducing the risk of ill health and preventable deaths thereby contributing to the nation's wealth. The health sector aims to achieve this through an efficient health system, which can deliver an internationally acceptable standard of health services. ¹⁰

¹⁰(See Ministry of Health, Ghana: Health Sector Medium Term Development Plan 2014-2017.

It is important to note that, in the context of sector specific policy frameworks, Ghana is working towards the trajectory of sustaining the gains, and fully achieving the MDG 4 and 5 which are recaptured in goal 3 of the Sustainable Development Goals (SDGs) as "Good Health and Well-being"¹¹. Therefore, maximization of population health outcomes, especially production of maternal health and achieving the aforementioned goals are not exclusively mutual.

One important issue in DEA programming is the scale of operation in the production of health or health care. From the production economics theoretical point of view, a technology may exhibit either a constant, increasing or decreasing returns to scale. 1 is based on the constant returns to scale (CRS) assumption which is the CCR model proposed by Cooper et al. [18, See eg. pp. 76]. The constant returns to scale assumption first widely used in DEA empirical analysis and is based on the proposition that, all DMUs are operating at an optimal scale (Pareto-Efficiency). However, typically of the health sector, the market is characterized with an imperfection where information asymmetry is obvious. Issues such as constraints on finance, and regulatory constraints on entry, mergers and exits may often lead to health care systems operating at an inefficient scale Rowena et al. [31, 32, 33, chap. 5]. Kirigia [36, 37, 38, 39, pp. 117] postulates that, the constant returns to scale assumption may not often be valid for health care systems' DMUs. According to Subhaash [52, 53], the CRS assumption is rather restrictive because it is unlikely that it will hold globally in many realistic cases and that should not be applied in a wide variety of situations.

Like a common practice in the corporate world, measuring performance in the health care systems over time is imperative. Characteristically about the health sector, major policy changes, epidemiological transitions, changes in government, climate change etc; might impact on the performance of the health care systems either positively or negatively. Thus, in order to measure changes in health care systems productivity and efficiency over the period 2001-2014, we applied Total factor Productivity Growth Index (MTFPGI) one of the widely used methods to measure productivity growth (technical changes) over time. Malmquist tool was first introduced by Malmquist in 1953. Caves et al. [17], expanded it to productivity measurement index and introduced into a DEA-Malmquist performance measurement by Fare et al. [22]. Following Ramanathan [50, 51], the output based MPI is defined as:

$$M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{(D^t x^t, y^t)} \times \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \quad (3)$$

Where D^t is the distance function measuring the efficiency of conversion of

¹¹The goal 3 of the Sustainable Development Goals is health related tagged "Good Health and Well-being"

inputs x^t to inputs to outputs y^t during the period t . If there is a technological change during the period $(t + 1)$, then, $D^{t+1}(x^t, y^t)$ = Efficiency of conversion of health inputs at period t to health output at period t $D^t(x^t, y^t)$. The MPI can be decomposed into the overall efficiency measures that are exclusively mutual. The components are change in efficiency change (EFFCH) (catch-up) emanating from good management practices and technological change (TECH) (frontier-shift) stemming from technological innovations within the health care systems. We modified 3 to reflect the two major components of the Malmquist Productivity Index as:

$$M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \right]^{\frac{1}{2}} \quad (4)$$

The first half of Equation 4 measures changes in EFFCH of the MPI from t to $t + 1$. That is to say it measures how the health related-DMU being investigated have worked to catch up to the efficient frontier. The other half in the square brackets (TECH) measures the technical component of the MPI. In fact, it represents the measurement of changes in the health or health care production frontier (a shift in best-practice technology innovation) from period t to $t + 1$. The TECH is the geometric mean of the shift in the production frontier observed between y^t and y^{t+1} .

The MPI can be written in a more compact algebraic equation form with its mutually exclusive two components as:

$$MPI_{it} = EFFCH_{it} \times TECH_{it} \quad (5)$$

where MPI_{it} is the Malmquist Productivity Index of i^{th} DMU at time period t , $EFFCH_{it}$ is the efficiency change of i^{th} DMU in period t and $TECH_{it}$ is the technology efficiency change of i^{th} DMU in period t . Thus, the MPI_{it} measures the Total Factor Productivity Growth. If the value of MPI_{it} is greater than a unity, then, there an evidence of technical progress in the production of health outcomes. Clunies et al [28], defines technological progress as *new invention or innovation that makes possible the production of higher output with the same amount of labour and capital as before*. Furthermore, a value of MPI_{it} less than unity is interpreted as a decline in productivity growth (i.e. technical regress). On the other hand, an MPI_{it} equals to unity means no change in TFP¹²

4.2 Random Effect Panel Tobit Model

In the second part of this paper, we utilize the random effect (RE) panel tobit model to investigate the effect of the NHIS, and total fertility rate (TFR) on

¹²See, eg. Caves et al.(1982) and Fare et al.(1994)

MPI_{it} . Using the RE panel tobit, we specify the latent variable y_{it}^* to depend on these regressors, and idiosyncratic error, and an individual-specific error, so

$$\begin{aligned} y_{it}^* &= \mathbf{X}_{it}'\beta + \alpha_i + \epsilon_{it} & i &= 1, 2, \dots, N \\ & & t &= 1, 2, \dots, T \end{aligned} \quad (6)$$

where $\alpha_i \sim N(0, \sigma_\alpha^2)$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ and the vector \mathbf{X}_{it} includes NHIS, TFR and an intercept. The left censoring at 0, we observe the y_{it} variable, where

$$\begin{cases} y_{it} = y_{it}^* & \text{if } y_{it}^* \geq 0 \\ 0 & \text{if } y_{it}^* \leq 0 \end{cases} \quad (7)$$

the α_i captures the regional specific unobserved inputs assumed to be constant over time, and ϵ_{it} is an idiosyncratic error which varies across time and regions.¹³

The equation we estimate is as follows:

$$MPI_{it} = \beta_0 + \beta_1 TFR_{it} + \beta_2 NHIS_{it} + \alpha_i + \epsilon_{it} \quad (8)$$

where MPI_{it} is the Malmquist productivity index, obtained using the DEA. i and t represent region and time, respectively, while α_i is the individual fixed effect and ϵ_{it} is the error term.

5. VARIABLES AND DATA

One of the crucial and challenging concerns in carrying out a technical efficiency study through DEA methodology is the selection of *the most appropriate health or health care production input and output variables*. Common among the previous literature on this subject matter, the most frequently used population health outcomes are maternal mortality ratio, infant and under-five mortality rates, life expectancy at birth, life expectancy at 60, life expectancy at 65 and healthy life expectancy. Furthermore, Quality-Adjusted Life Year (QALY), Disability-Adjusted Life (DALY), Healthy-Years Equivalent (HYE), Standardized Death Rate (SDR) and incidence of tuberculosis have been used in employed in studies as health outputs. For instance, Medeiros et al. [42, 43] used Life expectancy at birth, Life expectancy at age 65, Healthy life expectancy at birth and Amenable mortality in their study as population health outcomes and per capital health expenditure measured in Purchasing Power Parity international dollar (PPP) as health service production inputs. In our paper, the single health output is modelled to depend on the two inputs (human resources) of the regional

¹³For details on RE [41].

health care systems which reflect the health sector policies implemented by the national health authorities over the years in line with various policy directions.

The data for this study were obtained from the the annual regional health care systems reports and factsheets compiled by Ghana Statistical Service (**GSS**), Ministry of Health (**MOH**) and **GHS**. We collected balanced panel data on number of doctors and number of nurses as potential proxy of the regional health service production inputs; while data on institutional maternal mortality was used as a single output variable from 2001-2014

According to Joumard et al.[35], the resources that determine population health status can be measured in monetary terms, or physical terms, lifestyle factors and socio-economic factors. It is important to add here that, human resources fundamental and critical components of the health production technology. We selected our input and output variables based on six main restrictions in this study. First, currently in Ghana, there are no data on regional health care expenditure per capita. So we lack data on inputs measured in monetary terms (no regional health inputs price information). And therefore we proxied our health production inputs from the ten regions in terms of human resources. Second, Institutional Maternal Mortality Ratio is an output from the health care systems and therefore fits our theoretical model and other **DEA** relevant assumptions. The use of iMMR is also a fair opportunity of assessing the possible existence of inequality in accessing health care services across the ten regions. Third, sometimes the use of macro population health outcomes data may not be representative enough. And therefore using regional level data will possibly bring our study fairly closer to the micro level of analysis which is more representative of the population. Fourth, the two inputs variables are discretionary. That is, they are directly under the auspices of the health policy makers and development planners. Fifth, the philosophy underpinning the development of **DEA** technique was to measure the relative technical efficiency of the a set of decision making units when the price data for inputs and outputs are either unavailable or unknown Jati [54]. Six, the data for the chosen variables are a available from the ten regions for quite a long period (2001-2014) for short-term, medium-term and long-term efficiency and productivity growth analysis using panel data.

The samples constituting the decision making units are Ashanti Region (**AR**), Brong Ahafo Region (**BA**), Central Region (**CR**), Eastern Region (**ER**) Greater Accra Region (**GAR**), Northern Region (**NR**), Upper East Region (**UER**), Upper West Region (**UWR**), Volta Region (**VR**) and Western Region (**WR**). They are the ten administrative regions in Ghana whose health care systems performance are compared in the study. The choice of sample size is to ensure that the relative efficiency scores are not compromised by the problem of degree of freedom. In **DEA**, the number of degree of freedom increases as the number of DMUs increase and vice-versa. From the statistical points of view, this characteristics of **DEA** can distort the stability of the efficiency score. Thus,

we follow the suggestion proposed by Cooper et al. [20] that is a rough rule of thumb which can provide guidance to choose a value of n that satisfies $n \geq \max[m \times s, 3(m + s)]$, where n is the number of DMUs, m is number of inputs and s is number of outputs.

Table 1: Summary Statistics for the Variables used in the Study: Ten Regional Values for 2001-2014

Variable		Mean	Std. Dev.	Min	Max
Nurse	overall	1806.857	1155.141	326	6202
	between		1016.857	632.8571	4130.357
	within		630.1258	46.5	4010.286
Doctor	overall	181.4786	273.0359	9	1651
	between		256.2608	14.78571	823.7857
	within		122.5592	-276.3071	1008.693
iMSR	overall	571.8562	190.6551	48.8753	1297.701
	between		74.76154	475.5613	705.0308
	within		176.8695	71.05641	1271.995

Table 1 represents the descriptive statistics for the regional panel data on number of nurses, doctors and Institutional Maternal Survival Ratio (iMSR). There is at least some statistical evidence of inequality and inequity of human resources and consequently the outcome of the regional health service production proxied by the number of nurses, doctors and iMSR respectively. In terms of number of nurses observed from 2001 to 2014, the overall mean and standard deviation were 180.857 and 1155.141 respectively. This indicates that there is a significant variation in terms of the number of nurses across the ten administrative regions in Ghana over the period of consideration. As indicated in the introduction section, the distribution of health professionals are skewed towards the urban and rich regions creating regional inequality in terms health personnel allocation. Another important welfare regional comparative analysis from **Table 1** is the summary of the number of doctors across the ten regional health care systems. The overall mean and standard deviation over time and across the regions were 181.4786 and 273.0359 respectively. It can be inferred that the overall standard deviation of the number of doctors is greater than the overall mean of the number of doctor temporally and spatially. A standard deviation greater than the mean is an indication at least statistically that, the range of the regional health care system with highest number of doctor relative the regional health care system with the least number of doctors is so big as can be inferred from the minimum and maximum column from the table. The same result could be arrived at using the between and within mean standard deviation from **Table 1**. Another significant statistical information

from **Table 1** is the **iMSR**. A summary on **iMSR** indicates the annual number of female that survived per 100,000 live births. For the **iMSR**, the overall mean and standard deviation were 571.8562 and 190.6551 respectively. The minimum and maximum for the period 2001 to 2014 were 48.8753 and 1297.701 respectively. This again suggest that, there is a greater variation in terms of **iMSR** over time and across the individual regional health care systems under investigation. It is evidentially proving from **Table 1** that, inequality within each regional health care system measured by the **iMSR** over time was greater than from one region to another (between variation) ($176.8695 > 74.76154$). The result seems to approximating the fact that, the regional trends of Institutional Maternal Mortality Ratio (**iMMR**) and for that matter **iMSR** distribution has not witnessed a paradigm shift in spite of a number of universal health coverage and health system equity policies been put in place over the years.

The **DEA** methodology follows the *isotonicity* principle. “The assumption that, the relationship between inputs and outputs not be erratic. Increasing the value of any input while keeping other factors constant should not decrease any output but should instead lead to an increase in the value of at least one output”¹⁴. In health production, institutional maternal mortality ratio is considered to be an undesirable output (bad-output). Gomes and Lins [24] opined that, *an undesirable output is an undesirable result of a productive process, whose production must be minimized*. On the moral sense, it will be undesirable to maximize maternal mortality ratio. But an attempt to minimize an output will also raise theoretical questions and evidence of methodological conflict.

Efficiency evaluation methods assumed in our paper indicate that health output is maximized in such a way that the principle of "more is desired" is theoretically adhered to. Afonso and Aubyn [12] in their study involved Infant Mortality Rate (**IMR**), an undesirable health output. They transformed the data into “ Infant Survival Rate (**ISR**)” using the formula:

$$ISR = \frac{1000 - IMR}{IMR} \quad (9)$$

and interpreted the result as the ratio of children that survived the first year to the number of children who died, and that, **ISR** increases with a better health status. Following the above procedure, we transformed the **iMMR** which is defined as the annual number of female deaths per 100,000 live births from any cause related to or aggravated by pregnancy or its management (excluding accidental or incidental causes) to "Institutional Maternal Survival Ratio" in a given year with reference to a particular health-related DMU ($iMSR_{it}$).

Thus,

$$iMSR_{it} = \frac{100,000 - iMMR_{it}}{iMMR_{it}} \quad (10)$$

¹⁴Sourced from: <http://deazone.com/en/isotonicity>

The interpretation of **10** is straight forward. It is the annual number of female that survived per 100,000 live births. Contrary to the ($iMSR_{it}$), (the lower the better), with better and a more efficient health care system, holding all else constant, this is expected to be on the increase.

6.0 EMPIRICAL RESULTS AND DISCUSSIONS

We employed output-oriented **BCC** model and used **DEA-Solver**, Learners-Version (L-V8) software to calculate the relative efficiency of the regional health care systems. As indicated in the literature review, sometimes a 1-year time lag may not be enough to observe the full impact of important policy, technological innovations, and other organizational changes that may affect the performance of the health care systems. This is often quite than not the case when dealing with issues of impact lag¹⁵ and composite social development indicators such as maternal death, life expectancy, under-five mortality rate ect. Thus, we present technical, technological and productivity changes using a ten-year moving average scores trends with intention of capturing at least short-medium-terms policy effectiveness across the the regional health systems specifically those that are maternal health production biased.

6.1 Efficiency Change (Catch-up)

Under the assumption of **BCC-DEA** and output-orientation model as discussed in the methodology section, **Table 2** reports statistics of the performance evaluation of the ten regional health care systems for the periods 2001 to 2014. The “Catch-up”, “Frontier” and “Malmquist” denote efficiency, technical and productivity changes respectively. The standard deviation describes the variations relative to how each region is able to use its scarce human resources and other inputs mix to promote maternal health. In terms of Catch-up (managerial efficiency change), the variation between the regions is about 49.4%. The spread of performances regarding the Frontier-shift (technological efficiency change) and the Malmquist (total factor productivity growth) are about 23.2% and 36.1% respectively as can be inferred by **Table 2**.

Catch-up (Efficiency Changes)

The relative TE score >1 implies efficiency is increased from 2001 to 2014, <1 implies TE is decreased from 2001 to 2014 and $TE = 1$ means no change in efficiency from 2001 to 2014. The average TE change for the entire sample is 1.1226. This result reveals that, on average the TE of the ten regional health care systems improved by about 12.6%. As per the direction of this paper, it is imperative to compare each regions's performance relative to the maternal

¹⁵Impact lag is the time it takes any change initiated by a government policy to impact the a given sector in the economy

Table 2: Efficiency, Technical and Productivity Change: 2001-2014

Region	Catch-up	Frontier	Malmquist
AR	1.2128	1.3957	1.6927
BA	0.8585	1.2267	1.0531
CR	2.3188	0.8808	2.0423
ER	0.8888	1.6177	1.4378
GAR	0.6092	1.4679	0.8942
NR	0.9684	1.3246	1.2828
UPER	1.5529	0.9566	1.4855
UPWR	1.0000	1.2200	1.2200
VR	1.0634	1.5011	1.5963
WR	0.7535	1.2395	0.9339
Average	1.1226	1.2831	1.3639
Max	2.3188	1.6177	2.0423
Min	0.6092	0.8808	0.8942
SD	0.4934	0.2323	0.3609

health production frontier (frontier efficiency). It is evident from **Table 2** that 40% (4/10) of the DUMs experienced increased in TE; 1% (1/10) is efficient but no change in TE while 50% (5/10) of the DMUs witnesses a decline in TE from 2001 to 2014. Among the ideal performing regional health care system CR recorded the highest performance improvement score.

In terms of worse performing regions, it is important to provide a simple classification of the relative efficiency scores that provides insights for easy understanding for the reader. Following Yang [?] we classified the inefficient DMUs as follows: DMUs with an efficiency rating in excess of 0.9 however less than 1.0 is described as *marginally inefficient* and could raise their score towards the efficient frontier with relatively small amount of improvement in their production outputs. A TE score that falls between 0.7 and 0.9 are classified as *medium inefficient* units. With regards to our result as in **Table 2** BA, ER, NR and WR are classified as medium inefficient regions. Meaning that those four regions were not severely distanced away from the efficient frontier. A DMU with relative TE score less than 0.7 is classified as *distinctively inefficient* units. We therefore classified GAR as *distinctively inefficient* region in the sample units. Yang opined that “if the efficiency score of a unit is less than 0.7, then this unit would have significant difficulties making themselves efficient in the short term”. Juxtaposing our findings with MOH 2015 report [44], we able to at least confirm empirically that, GAR was *distinctively inefficient*. The performance as per the relative efficiency scores of the DMUs seems to on average support MOH 2015 remark that, “Institutional maternal mortality was as high as 174

deaths per 100,000 live births in 2011 but has since then dropped to 144. There are large regional variations in iMMR. The highest is in Greater Accra Region (185) followed by Volta Region (179) and Easter Region (176)."

Frontier-shift (Technological Changes)

As indicated in the text, a health care unit is described technically efficient if it succeeds in reducing iMMR (increasing iMSR) without increased in inputs (number nurses and doctors in our case)utilization. In fact technical efficiency is analogous to economization of scarce health resources. **Table 2** reveals that between 2001 and 2014, 20% (2/10) of the regional health care systems registered Technical Change (**TECH**) less than unity, implying decline in technological innovation. 80% (8/10) of the sampled regions recorded various degree of positive technical changes with the ideal performing region scoring a maximum of 61.8% (1.6177). The overall average **TECH** was 28.31%. This impressive growth is more than 50% of Efficiency Change (**EFCH**).

Malmquist (Total Factor Productivity Growth)

For the estimation of the calculation of the Malmquist Total Factor Productivity Index, the year 2001 was chosen as the reference technology year t in order to evaluate the changes in regional health care systems productivity over time. Column 4 of **Table 2** presents geometric mean of productivity growth over the 13 years of observation.

Overall, over the 13 years period, the sampled regions experienced growth in productivity which is indicated by the avarage **MTFPGI** score of 36.39% (1.3639-1) with a standard deviation of about 36.1%. Since the **MPI** is the product of **EFCH** and **TECH**, it is important to trace the sources of technical progress or technical regress. It can can be seen from **Table 2** the overall average **EFCH** <**TECH**, it implies that on average the improvement in productivity growth across the ten regions are largely due to technological innovation.

When the regions are considered individually, the results show that 30% (3/10) namely: **CR**, **UWR** and **VR** derived their technical progress from both improvement in Catch-up (technical efficiency) and Frontier-shift (technological efficiency). It is also evident from **Table 2** that, the two regions **GAR** and **WR** witnessed technical regress evidentially emanating from 39.1% and 24.6% decline **EFCH** respectively.

6.2 The effect of **TFR** and **NHIS** on **DEA** Efficiency

The preceding subsection provided the results of the efficiency, technical and productivity changes over time for the 10 regions of Ghana. Over here, we take a second step to explore the determinants of efficiency for the regions. Specifically, we are interested in the effect of environmental factors such as **TFR** and **NHIS** on the productivity growth across the health care systems under investigation.

The **TFR** represents the number of children a woman would have if she lived

through all her childbearing years and experienced the current age-specific fertility rates at each age (Weil [56]). We are particularly interested in this variable because it affects both child and maternal health. Hence, we assume that a higher **TFR** may impact negatively on the **MTFPGI**. The second variable of interest is the **NHIS**. The **NHIS** has made health care affordable and greatly contributed to the increase in usage in Ghana (Amponsah [14, 15]) . But, how does it affect efficiency and productivity in the health care systems of Ghana? Our **RE** specification will help us answer this question.

Table 3: *Random Effect Tobit Estimation Results: 2001-2014*

Variable	Coefficients	Std. error
TFR	-0.099198	0.1607657
NHIS	-0.3279378	0.2428022
Year	-0.0839358**	0.0380836
NHIS#year	0.0855916**	0.0420193
$/\sigma_u$	1.20e-18	0.0215037
$/\sigma_e$	0.2448046	0.0212556
rho	2.41e-35	1.12e-19
Wald Chi2(4)	25.17	
Prop>Chi2	0.0000	

Table 3 reports the estimates of our environmental factors on **MTFPGI**. Our specification includes time-invariant variables and interaction term between year and **NHIS**. Column 1 of Table 3 provides the coefficients of our results and column 2 reports the bootstrap standard errors. The chi-squared test statistic result of 0.1% significance level presented in Table 3 indicates that our **RE** model is significant and that the variables used are significant determinants of the **MTFPGI** in Ghana. The σ_u is the standard deviation of the time-invariant individual-specific term α_i , and σ_e is the standard deviation of the error term ϵ_{it} (i.e., the panel-level variance), while rho is the percentage contribution to the total variance of the panel-level variance component. If rho is zero, the panel-variance component is unimportant, meaning the panel estimator is not different from the pooled estimator, as our results show, the panel data structure of the model can be ignored because rho is zero.

Our result shows that **TFR** has an insignificant effect on the **MTFPGI** and the coefficient is -0.099, which may indicate that high **TFR** may decrease efficiency and productivity. Also, the **NHIS** dummy has a statistically insignificant negative coefficient. This result may reveal that implementing a health insurance policy in a region can increase the inefficiency and decrease productivity.

The year variable is also negative and statistically significant, while the

interaction between the year and **NHIS** variable is positive and significant, showing the positive effects of **NHIS** on efficiency and productivity.

6.3 DISCUSSION AND GLOBAL IMPLICATIONS

The perceived existence of inefficiency in the health care and health service production has received attention of health policy makers and international organizations such as the **WHO** [19], as the global health needs keep on appreciating especially in the developing world in the face of limited health inputs. Consequently, the measurement of efficiency and productivity as an explorative mechanism of assessing performance of health care systems has widely been applied over the few decades as standard tool for performance assessment and monitoring. Since inefficiency is not directly observable, such timely empirical evaluation and monitoring health care units performance has become relevant to health care planners and administrators. For instance, comparing health care systems' performance within and across nations could be a litmus paper to indicate how the various health systems perform relative to potential peers and measuring productivity over periods of time can give insights into whether productivity is appreciating or depreciating for proactive policy action to be initiated.

In the same direction, the main goal of our paper was to assess efficiency and productivity growth of the ten administrative regional health care systems from 2001 to 2014 in the Republic of Ghana. We estimate technical and technological changes using **DEA** tool. We applied a **DEA**-Malmquist productivity index to calculate TFPG over the period of analysis.

A key finding from this current study is that productivity of the ten regional health care systems considered in the study on average grew over the 13 years of observation. The impressive observed average MPI score of 1.3639 for the sampled regions during the period of analysis indicates that on average the regional health care systems improved over the 13 years of observation. The impressive observed 1.3639 for the sample regions during the period of analysis suggests that on average the regional health care systems increased their productivity by about 36.39%. Notwithstanding, growth in productivity fluctuates in the sub-periods. Readers interested in the trending patterns of the efficiency change (Catch-up), technological change (Frontier-shift) and total factor productivity growth index can infer from **Table 3**, **Table 4** and **Table 5** in the appendix column which we present ten year moving averages and **Figure 1** which shows the initial initial-final-year Malmquist productivity index.

Our findings suggest that growth in productivity relative to the decompositions of the **MPI** for the entire sample was largely due to technological progress instead of technical efficiency improvements pinpointing to the fact that there is additional scope for further reduction in **iMMR**

especially in the Greater Accra Region.

In growth accounting or production economics broader sense, technological change (innovation-led growth), the main conduit of productivity growth is basically related to strategic investment. That is change in real capital stock. Evidence of capital accumulation occurs when states, firms or organizations invest in modern-efficient equipments, machinery and physical structures that provide the opportunities to produce more outputs. Consequently, this causes shift in the production frontier to the optimum level. We are able to show from our results during the study that, the regional health care systems constituting our **DMUs** experienced technological progress. This results in social benefit-reduction in **iMMR** (increased **iMSR**) in majority of the regions. The technical progress made across the various regional health systems could, at least theoretically be attributed to the various health reforms especially those in line with **MDGs** goal 4 such as **CHPS**, **NHIS**, train and retain policy which allow professional nurses and midwives trained in the various region to pick up employment in their respective regions; improvements in medical technologies; political economy of maternal health service production; and intervention by non-state institutions especially programmes that focused on the three most deprived Northern Regions.

Our data revealed that, from 2001-2014, the number of doctors and nurses increased hence causing downwards trend in the regional doctor and nurse patient ratios though regional inequality and inequity have not witnessed a paradigm shift. This seems to suggest that increased in quality and quantity of the health workforce across the ten regions in Ghana was key in technological progress.

The results of our current study have some interesting policy implications for the development of the regional health care systems in Ghana particularly in addressing region-specific maternal health service needs. We would want emphasize in our paper that the potential outcomes of this study are essentially conditioned on the selection of health care production inputs; and transformation of the output data and; therefore all policy implications stated beneath shall be considered within this context.

Our study indicates that, among the inefficient regional health care systems, **BA**; **ER**; **GAR**; **NR** and **WR** would have to increase their managerial efficiency by about 14.2%, 11.1%, 39.1%, 3.16% and 24.7% respectively in order catch-up with the production frontier (efficiency frontier) especially by learning from **CR** which was the most ideal decision making unit from 2001 to 2014. Thus, there is room for improvements by **MOH** and **GHS** policy makers to improve efficiency and productivity in those stated inefficient regional health care systems by putting their scarce health care inputs in judicious use.

Findings from our **RE** tobit estimation indicates that both the **TFR** and the **NHIS** have negative effects on **MTFPGI**. For the former, it implies that higher **TFR** has detrimental effect on efficiency and productivity when one considers

the health systems of Ghana. On the **NHIS**, it could be argued from policy perspective that its implementation has resulted in equitable health care usage, however, the negative effect on the **MTFPGI**, although insignificant, brings to light the issue of balancing equity with efficiency. We can argue that the NHIS has brought about an over-stretch of limited health care resources such as increased workload on nurses and doctors. The increased in outpatient, inpatient and per capita visit since the introduction of the NHIS has negative tendency of reducing productivity of the health care systems under investigation. Another perspective could be that the NHIS policy is not efficiently addressing its pro-poor concept and therefore suffers from policy inefficiency hence its negative relationship with the **MTFPGI**.

CONCLUSION

This current paper explicates efficiency and productivity growth in the regional health care systems in Ghana over a 13 year period from 2001 to 2014. It is also imperative to note that our analysis is based on fairly micro-level data which is likely to give a more comprehensive state of affairs regarding the regional health systems performances relative to reducing institutional Maternal Mortality Ratio. By applying **DEA** methodology we estimate technical efficiency, technological efficiency and **DEA**-Malmquist based Total Factor Productivity Index. We decomposed Malmquist Total Factor Productivity Index into its mutually exclusive components namely: average efficiency change (Catch-Up) and average technological change (Frontier-Shift) under the assumption of Variable Returns to Scale (**BCC-DEA**). We also performed a **DEA**-tobit regression to estimate the impact of environment factors on the productivity growth across the health care systems under investigation.

The results indicate that the mean total factor productivity index of the regional health care systems of our sample grew over the 13 year period; and that this recorded growth was largely due to technological growth rather than efficiency change as indicated by the means of Catch-Up and Frontier-Shift in **Table** . The empirically observed mean **MTFPGI** score of 1.3639 for the **DMUs** during the study period shows that on average the regional health care units increase their productivity by about 36.39% in each adjacent year. In addition, the results indicate growth in total factor productivity to greater extent was due to technological progress rather than managerial efficiency improvements. Juxtaposing our results with the macro population health data on the trend of Maternal Mortality Ratio, we are able to conclude that Ghana's recent report on the downward trends of Maternal Mortality Ratio reflects improvements in the performance of the regional health care systems. However, we unexpectedly saw in our results that Greater Region whose doctor patient ratio and nurse patient ratio are close to the World Health Organization's prescription was the

worse performing region. Our results on average reaffirms Ministry of Health 2015 Hoslistic Health Assessment's report that: *“Institutional Maternal Mortality Ratio was as high as 174 deaths per 100,000 live births in 2011 but has since then dropped to 144 in 2014. There are large regional variations in iMMR. The highest is in Greater Accra Region (185) followed by Volta Region (179) and Easter Region (176)”* and therefore policy makers must as a matter of concern intervene in Greater and other poor performing regions with an immediate policy interventions and maternal health service production more especially in areas where managerial issues are mattering. Our **DEA**-tobit regression analysis indicates that both **TFR** and **NHIS** have negative effect on efficiency and productivity growth index (i.e., **MTFPGI**). Thus, it provides a framework for considering policy option. Hence, we would like to associate with some of the policy options that have been suggested over the years for prompting fertility decline. Especially, those in the areas of education that are directed at reducing the demand for children and, others, such as encouragement of later start of childbearing, which influence fertility by reducing exposure to the risk of conception. In the case of the **NHIS**, we recommend that policymakers' should find a way of balancing equity with efficiency. Without that it will be difficult for the health systems of Ghana to be efficient and productive.

We applied **DEA** methodology to the relating inputs and output to evaluate efficiency and productivity growth from the views points of production economic and growth accounting. We however failed to address matters relating to allocative efficiency due to unavailability of price information. On the background that **DEA** has its merits and demerits, a parametric approach to efficiency and productivity, for instance, Stochastic Frontier Analysis (SFA) could be another empirical way of using our panel data to assess productivity growth in the regional health systems in Ghana. Again further research can be carried out using the number of midwives as an input into the production of maternal health across the ten regions of Ghana and compare the results with the current one reported in this paper.

ACRONYMS

SAPs Structural Adjustment Programmes.....	2
PHC Primary Health Care	2
MDGs Millinium Development Goals.....	1
DHDs District Health Directorates	2

TFPG Total Factor Productivity Growth.....	1
MTFPGI Malmquist Total Factor Productivity Growth Index	12
NHIS National Health Insurance Scheme	2
NHIA National Health Insurance Authority.....	5
CHPS Health Service Community-Based Health Planning and Services.....	2
WHO World Health Organization	2
TE Technical Efficiency.....	10
DMUs Decision Making Units	3
DEA Data Envelopment Analysis	1
OPD outpatients'	5
SDGs Sustainable Development Goals.....	12
MOH Ministry of Health	15
GHS Ghana Health Service	4
EFCH Efficiency Change.....	20
AR Ashanti Region.....	15
iMSR Institutional Maternal Survival Ratio	16

BA Brong Ahafo Region	15
CR Central Region	15
ER Eastern Region	15
GAR Greater Accra Region	15
NR Northern Region.....	15
UER Upper East Region	15
UWR Upper West Region	15
VR Volta Region	15
WR Western Region	15
IMR Infant Mortality Rate	17
ISR Infant Survival Rate	17
TECH Technical Change	20
iMSR Institutional Maternal Survival Ratio	16
GSS Ghana Statistical Service.....	15
MTFPGI Total factor Productivity Growth Index.....	12
MPI Malmquits Productivity Index	1

iMMR Institutional Maternal Mortality Ratio	17
FDH Free Disposable Hull	6
RE random effect	13
TFR total fertility rate.....	13
DHMT District Health Management Team	4
RHA Regional Health Administration or Directorate	4
DHA District Health Administration	4
OOP out-of-pocket.....	5
BCC Banker, Charnes, and Cooper	1
CCR Charnes, Cooper, and Rhodes	9

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Figure 1: Appendix A: Malmquist Index for 2001 and 2013

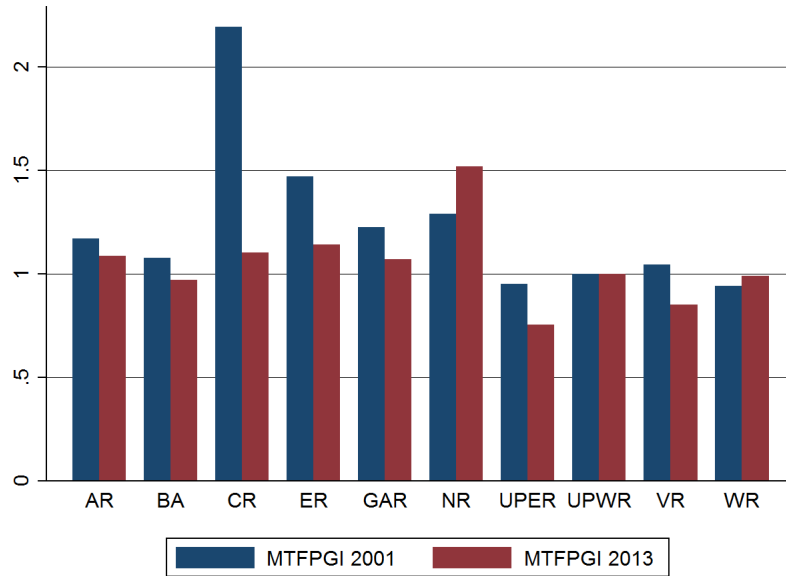


Table 4: Appendix B: A Ten Year Moving Average of Catch-Up: 2001-2014

Region	2001-2011	2002-012	2003-2013	2004-2014	Average
AR	0.7193	1.9081	1.9331	1.4374	1.4995
BA	0.9631	1.5203	1.7740	1.5740	1.4579
CR	1.9134	1.9373	1.6084	1.2492	1.6771
ER	0.7580	1.1215	1.6202	1.4192	1.2297
GAR	0.4168	0.0434	1.1648	1.0358	0.6652
NR	0.6039	0.8073	1.8905	1.5475	1.2123
UPER	1.5529	2.3484	2.0343	1.5860	1.8804
UPWR	1.0000	1.0000	1.0000	1.0000	1.0000
VR	0.9350	2.1767	1.9866	1.3905	1.6222
WR	1.1537	1.9444	0.2478	0.9428	1.0722
Average	1.0016	1.4807	1.5260	1.3183	1.3316
Max	1.9134	2.3484	2.0343	1.5860	1.8804
Min	0.4168	0.0434	0.2478	0.9428	0.6652
SD	0.4477	0.7245	0.5664	0.2463	0.3644

Table 5: *Appendix C: A Ten Year Moving Average of Frontier-Shift: 2001-2014*

Region	2001-2011	2002-2012	2003-2013	2004-2014	Average
AR	1.5761	1.1362	0.7788	0.9873	1.1196
BA	1.2109	0.8398	0.6352	0.7030	0.8472
CR	1.7009	0.8621	0.6648	0.8515	1.0198
ER	1.7965	0.9506	0.7496	0.9728	1.1174
GAR	1.4928	1.3374	0.8121	1.0549	1.1743
NR	1.5634	0.8384	0.5493	0.8035	0.9387
UPER	1.5709	0.4627	0.5289	0.6994	0.8155
UPWR	1.2742	0.8550	0.7164	0.8177	0.9158
VR	1.7566	0.8658	0.6928	0.9069	1.0555
WR	1.6768	0.8496	0.6349	0.8463	1.0019
Average	1.5619	0.8998	0.6763	0.8643	1.0006
Max	1.7965	1.3374	0.8121	1.0549	1.1743
Min	1.2109	0.4627	0.5289	0.6994	0.8155
SD	0.1934	0.2250	0.0928	0.1177	0.1203

Table 6: *Appendix D: A Ten Year Moving Average of Malmquist Productivity Index*

Region	2001-2011	2002-2012	2003-2013	2004-2014	Average
AR	1.1336	2.1679	1.5055	1.4192	1.5565
BA	1.1663	1.2767	1.1268	1.1066	1.1691
CR	3.2546	1.6701	1.0693	1.0637	1.7644
ER	1.3617	1.0661	1.2145	1.3806	1.2557
GAR	0.6222	0.0580	0.9460	1.0927	0.6797
NR	0.9442	0.6769	1.0384	1.2434	0.9757
UPER	2.4395	1.0866	1.0760	1.1092	1.4278
UPWR	1.2742	0.8550	0.7164	0.8177	0.9158
VR	1.6424	1.8846	1.3762	1.2610	1.5410
WR	1.9345	1.6519	0.1573	0.7979	1.1354
Average	1.5773	1.2394	1.0226	1.1292	1.2421
Max	3.2546	2.1679	1.5055	1.4192	1.7644
Min	0.6222	0.0580	0.1573	0.7979	0.6797
SD	0.7822	0.6279	0.3741	0.2084	0.3344