Discover Health Systems

Research

Cost efficiency of primary health care facilities in Ghana: stochastic frontier analysis

Kwadwo Arhin[1] · Eric Fosu Oteng-Abayie[2] · Jacob Novignon[2]

Received: 18 July 2023 / Accepted: 3 October 2023
Published online: 19 October 2023

Abstract
Primary health care (PHC) is a universally accepted key strategy to achieve universal health coverage (UHC) and Sustainable Development Goal 3 (SDG 3) due to its potential to produce a range of economic benefits through improved health outcomes, health quality, and health system efficiency. However, little evidence exists about the cost efficiency of primary health care facilities (PHCFs) in Sub-Saharan Africa. This study evaluates the cost efficiency of two main types of PHCFs in Ghana that are at the forefront of delivering PHC services to a greater proportion of the population: Community Health Centers (HCs) and Community-Based Health Planning Services (CHPS) compounds. The dataset we used for this study included 39 HCs and 55 CHPS facilities. Furthermore, it examines the factors that influence the cost efficiency of these facilities. The study applies the stochastic frontier analysis (SFA) technique to panel data. The estimated cost efficiency for HCs and CHPS is 61.6% and 85.8%, respectively. The study further revealed that facility size, medical staff density, and facility age are the main factors that explain the differences in the cost efficiency of PHCFs in Ghana. The study's policy recommendation is that the Ghana Health Service should consider utilizing modern technology such as telehealth and telemedicine to enhance access to PHC services for people living in hard-to-reach and densely populated communities. This strategic approach can significantly contribute to improving the cost-efficiency of PHCFs.

Keywords Primary health care · Universal health coverage · Cost efficiency · Stochastic frontier analysis · Ghana

1 Introduction

Compared to secondary health care, primary health care (PHC) offers greater accessibility to the community, including those from different social backgrounds. In areas where PHC services are unavailable, hospitals often face many patients seeking treatment for minor and major health issues. This leads to the misallocation of scarce resources such as specialized personnel and medical equipment, which are more suitable for life-threatening illnesses, to the treatment of minor ailments [1, 2]. According to the World Bank, 90% of all health needs can be effectively addressed at the PHC level, with only 10% requiring hospital-based services [3]. Numerous studies have demonstrated that countries and regions that prioritize primary health care (PHC) tend to have healthier populations [4–7]. Allocating resources towards provision of PHC services is a cost-effective strategy for achieving universal health coverage (UHC) as it can avert illnesses and

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44250-023-00044-8.

✉ Kwadwo Arhin, arhinkwadwo@gmail.com; Eric Fosu Oteng-Abayie, otengknust@aol.com; Jacob Novignon, jnovignon@gmail.com | [1]Department of Economics, Ghana Institute of Management and Public Administration, Accra, Ghana. [2]Department of Economics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.

improve overall health, thereby reducing the need for more expensive and complicated care. According to Starfield [8], investing in the establishment of high-quality, accessible, and equitable primary health care services represents the most pragmatic, efficient, and effective initial action for countries striving to achieve UHC.

In Ghana, the primary health care (PHC) system has made contribution to the marked reduction in maternal, neonatal, and child mortality, as well as deaths caused by illnesses like malaria, tuberculosis, HIV/AIDS, and vaccine-preventable diseases. Extensive evidence now exists to support the effectiveness of PHC, mainly for the most common causes of illness and death [6, 7]. PHC has been shown to lower total healthcare expenditures and enhance efficiency by improving access to preventative and promotional services, providing early diagnosis and treatment for a broad range of conditions, delivering people-focused care that addresses the individual's holistic requirements, and reducing avoidable hospital admissions and readmissions [8, 9].

While some progress has been made, the performance of primary health care (PHC) in Ghana has fallen short in many other aspects of care. For instance, while skilled birth attendance (SBA) increased from 76% in 2014 to 88% in 2022, nearly all women (98%) reported receiving antenatal care (ANC) in 2022. However, the percentage of children aged 12–23 months who were fully vaccinated against all basic antigens decreased from 77% in 2014 to 73% in 2022 [10]. The persistent and paradoxical health outcomes have been attributed to various factors, including weak performance management systems, the concentration of healthcare resources in a few developed regions, low productivity of the healthcare workforce, and inefficiency, causing the country to miss out on MDG targets for maternal and child health despite high level of investment in the PHC sector [11].

To fully realize the benefits of achieving the goal of UHC through PHC programs, it is crucial to understand the cost efficiency of PHCFs. However, there is a lack of comprehensive study on this topic, particularly from developing countries' perspectives. Although some studies have been conducted on the technical efficiency of PHCFs [12–21], no research has estimated the cost efficiency of PHCFs in sub-Saharan Africa (SSA) (refer to Additional file 1: Appendix S1 for a concise overview of the relevant previous literature). Nevertheless, PHCFs are regulated by the government in most SSA countries. In a sense, the government is largely responsible for the prices charged for the services they provide. Moreover, the government is involved in determining which communities get served. Demand for PHC services ultimately determines the number of primary healthcare services provided by a PHCF and its only flexibility is found at the input side: the PHCF is assumed to provide services at the lowest possible cost. These conditions justify the estimation of the cost rather than the technical efficiency of PHCFs [22]. This paper aims to address this gap in the literature by utilizing panel data to demonstrate the estimation of the cost efficiency of PHCFs.

2 Overview of the PHC system in Ghana

In Ghana, as well as in many other countries, the healthcare system follows a decentralized multi-level structure organized under a hierarchical pyramid consisting of five levels [23] (see Fig. 1). At the top of the health system lies the tertiary level, which comprises teaching and specialist hospitals providing specialized clinical and diagnostic care, emergency services, training, and referrals from regional and district hospitals. The secondary level of Ghana's healthcare system is mainly composed of regional and district hospitals and occupies the central position of the pyramid. It receives referrals from the primary healthcare level and provides secondary healthcare services including emergency, clinical, diagnostic, and other related services.

At the base of the hierarchical healthcare system are the Health Centers (HCs) and Community-Based Health Planning and Services (CHPS) compounds, providing the primary healthcare (PHC) needs at the levels of the sub-districts and CHPS zones, respectively, which provide the basic healthcare services to the majority of Ghanaians. Each administrative district is divided into sub-districts which are further divided into CHPS zones. The sub-district healthcare system is established in health centers with Sub-District Health Management Team (SDHMT), serving a population ranging between ten thousand and twenty-five thousand [24]. Each health center is staffed by physician assistants, general nurses, and midwives.

The CHPS compounds provide integrated basic primary healthcare services, including basic disease diagnosis and treatment services, maternal and child health (MCH) services, health promotion, and disease and injury prevention services [25]. Each CHPS compound is staffed by midwives, community health nurses, and community health volunteers, and typically has a catchment population ranging from three thousand to five thousand [26]. HCs and CHPS compounds serve as the first point of call for people with health concerns. An administrative district with a population of 100,000 usually has one hospital, five HCs, and about 10 to 15 CHPS zones.

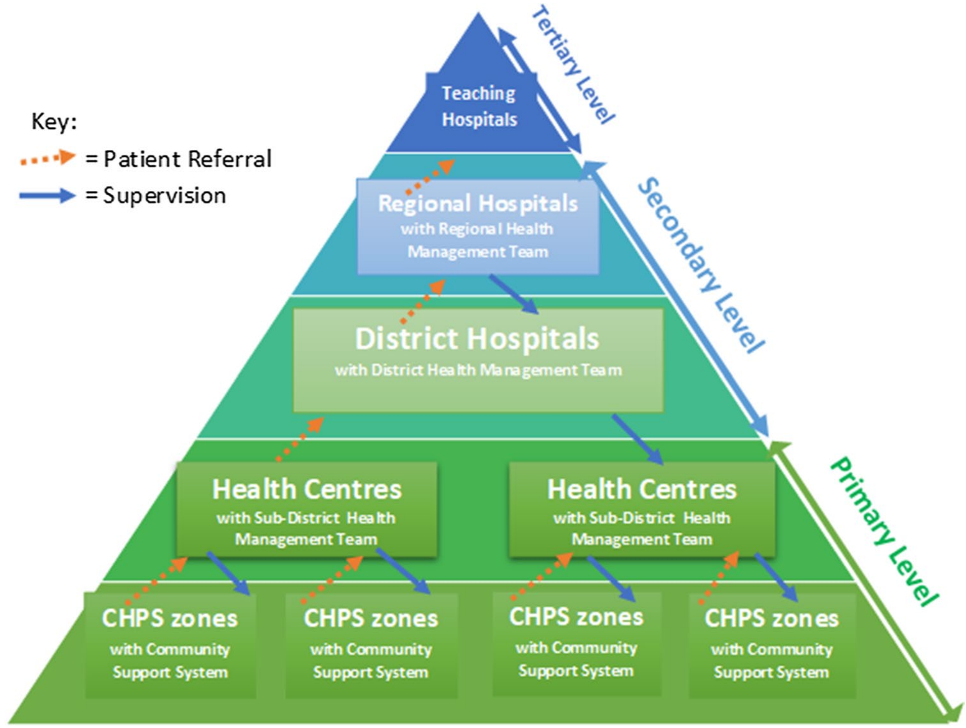


Fig. 1 Five-level hierarchical pyramid of Ghana's healthcare system (Adapted from Seddoh et al. [27] and Awoonor-Williams et al. [23])

The World Health Organization (2021) defines PHC as "*a whole-of-society approach to health that aims at ensuring the highest possible level of health and well-being and their equitable distribution by focusing on people's needs and as early as possible along the continuum from health promotion and disease prevention to treatment, rehabilitation and palliative care, and as close as feasible to people's everyday environment*". In line with this definition, several past research projects and policies have contributed to the current shape and form of Ghana's PHC system (see Fig. 2).

In the 1960s and 1970s, the government of Ghana, in collaboration with religious organizations, rapidly expanded access to PHC services through an increase in the number of healthcare facilities, the extension of mobile clinics to rural and underserved communities, and the training and posting of village health workers across the country [24]. The findings of three projects—Basic Health Services Project (1967–1971), the Danfa Comprehensive Rural Health and Family Planning Project (1970–1979), and the Brong-Ahafo Rural Integrated Development Project (1975–1979)—also significantly contributed to the design of current Ghana's PHC strategy of the three-tier district health system comprising the community level (CHPS zone with community support), the sub-district level (health center with Sub-District Health Management Team), and the district level (district hospital with District Health Management Team) [24, 28].

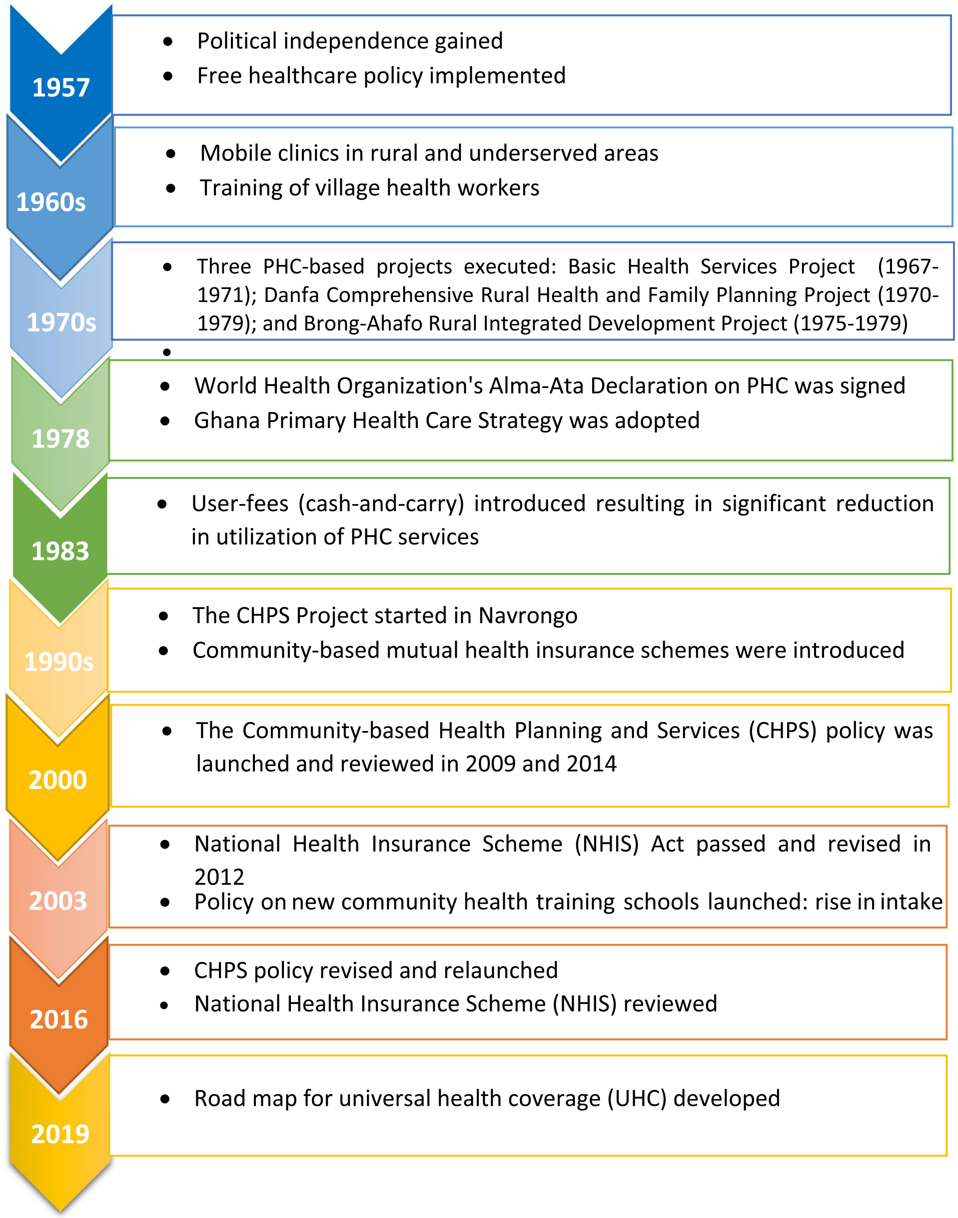
In 1978, Ghana adopted the Alma-Ata Declaration by the World Health Organization, which prioritized a healthcare system focused on PHC [29]. Since then, Ghana has been dedicated to achieving health for all by implementing the Ghana Primary Health Care Strategy in 1979, launching the Community-Based Health Planning and Services (CHPS) program in 2000 to improve access to healthcare services in rural and underserved areas, and establishing the National Health Insurance Scheme (NHIS) in 2003 to increase financial access to healthcare services (revised in 2012). However, Ghana's PHC system is facing challenges such as insufficient funding, the distance of CHPS compounds from communities, and a lack of essential logistics [30].

3 Materials and methods

3.1 Data and sampling design

We used data from the Access, Bottlenecks, Costs, and Equity (ABCE) Facility Survey in Ghana. This survey was part of a project involving the Ministry of Health (MoH), Institute for Health Metrics and Evaluation (IHME), Ghana Health Service (GHS), and UNICEF [31]. The project received ethical clearance from the Ghana Health Service. The survey gathered information from a wide range of health facilities across the country. The data collection occurred between

Fig. 2 Timeline of key developments in primary healthcare (PHC) system in Ghana



June and October 2012, with facility administrators answering the questionnaire. The sampling process included two stages and aimed to represent both rural and urban areas.

In the first stage, one rural and one urban district were randomly chosen from each of the then ten regions of Ghana, totaling 20 districts. Additionally, the Accra and Kumasi metropolitan areas were purposively included [31]. In the second stage, various health facilities were considered. These facilities included teaching hospitals, regional referral hospitals, general hospitals, health centers (HCs), Community-Based Health Planning and Services (CHPS), maternity clinics, pharmacies, drug stores, and District Health Monitoring Teams (DHMT). A sampling frame was established based on the 2011 Ministry of Health (MoH) Needs Assessment. In each of the districts sampled in the first stage, four hospitals, Health Centers (HCs), Community-Based Health Planning and Services (CHPS) facilities, maternity clinics, and two pharmacies were randomly sampled in the second stage. Two hundred and twenty (220) out of the total of 240 facilities sampled responded to the questionnaire, leading to a response rate of 92% [31].

As there has not been any recent facility-based data available since then, we extracted data from this existing database to retrospectively assess the cost efficiency of primary healthcare facilities (PHCFs). The dataset we used for this study included 39 Health Centers (HCs) and 55 Community-Based Health Planning and Services (CHPS) facilities, spanning the years 2007 to 2011. This created a balanced panel of 195 observations for HCs and an unbalanced panel of 233 observations for CHPS facilities.

3.2 Stochastic frontier analysis

The SFA model employs regression analysis to estimate the cost frontier and evaluate the efficiency of a DMU using residuals from the estimated equation [32, 33]. The cost function establishes the technological relationship between the levels of output, input prices, and resulting costs. Econometric estimation using observed costs, outputs, and input prices reveals the level of costs that can be determined from the given levels of output and input prices [34]. The estimation of the cost frontier presumes that the boundary of the cost function is defined by "best practice" PHCF(s), indicating the minimum feasible cost for a given set of output and input prices. Any deviation from the "best practice" frontier is decomposed into two independent components: random (stochastic) error and the inefficiency term. Thus, the stochastic frontier splits the distance of an observation from the frontier into random error and inefficiency. The random error is a two-sided error term following the standard normal distribution, while the inefficiency term is a one-sided error term that follows a truncated distribution such as half-normal, truncated normal, gamma, or exponential [22] Maximum likelihood (ML) techniques estimate these parameters, which are then employed to estimate PHCF-specific efficiency.

The earlier literature focused on a production function established for cross-sectional data, but recent advances have been made to utilize panel data, including balanced and unbalanced panels, and time-varying technical efficiencies [35]. Other extensions have involved applying the methodology to cost and profit functions [36], using a single-stage approach to examine the determinants of the efficiency of DMUs rather than a two-stage approach [37], and non-parametric and semi-parametric approaches that do not require parametric assumptions on the functional form of production relationships [38, 39]. In this study, we use a single-stage approach to analyze the determinants of cost efficiency for PHCFs.

A significant advantage of SFA over DEA is its ability to differentiate between inefficiency and random noise errors. DEA, on the other hand, combines both sources of residuals and treats them as inefficiency. Furthermore, SFA permits statistical tests of inefficiency scores to determine their level of statistical significance. SFA has faced criticism for requiring the specification of the cost function and inefficiency term distributional form in advance. In practice, the Cobb–Douglas, translog, and multi-output distance functions are commonly used as cost-functional forms in empirical research. However, if the functional form is misspecified, it may result in inefficiencies that are confounded with random noise, thereby defeating the purpose of using SFA to separate the two [40]. For this study, the Cobb–Douglas cost functional form was found to be appropriate for the data.

3.3 Empirical strategy

A Primary Healthcare Facility (PHCF), such as a Health Centre (HC) or Community-Based Health Planning Service (CHPS) compound, serves as an aggregate production unit that transforms various inputs such as labor, capital, and supplies into primary healthcare services outputs. Because of the extensive range of primary healthcare services, an output measure must be established through aggregation. Outpatient visits, antenatal, and postnatal visits, family planning and RCH visits, immunizations, deliveries, and inpatient discharges are the most commonly used output measures [15, 18, 21]. However, due to the practical infeasibility of estimating a multi-product cost function with several outputs, a model with a restricted output choice specification is used [41]. Specifically, a single-output production process is assumed, with a composite output derived from the linear aggregation of all primary healthcare services. The model employs three input factors: labor, capital, and drugs and supplies.

Based on the above specification, the total cost frontier can be represented by the following cost function:

$$C = f\left(Y, P_L, P_K, P_D, d_T\right) \tag{1}$$

where C is the total annual expenditure; Y is the composite output index for the annual total PHC services provided; $P_L, P_K, and P_D$ are the prices of labor, capital, and drugs and supplies, respectively; and d_T is a time trend dummy variable to capture changes in cost associated with technical progress and other unobserved year-specific factors.

It is assumed that the cost function as stated in Eq. 1 is the result of cost minimization given the prices of the inputs and output. Thus, it should satisfy certain properties. Basically, the cost function must be non-decreasing in input prices and output, homogenous of degree one in input prices, and concave in input prices. The linear homogeneity assumption is satisfied by normalizing the total cost and input prices by the price of one of the inputs [42]. In this study, the price of drugs and other supplies (P_D) is considered as numeraire employed to normalize the total cost and prices of the other inputs (see Eq. 2). The concavity assumption is automatically satisfied by the use of the Cobb–Douglas cost functional form [22]. The other theoretical assumptions are verified after the estimation.

To empirically estimate the cost function in Eq. 1, the SFA models are generally specified as Cobb–Douglas or translog functional forms. Cobb–Douglas functional form is relatively less flexible, but it is parsimonious and automatically satisfies the concavity assumption [43]. In the case of cost frontier, even though the translog specification is more flexible and provides a second approximation of the underlying true cost function, it has problems because it is not parsimonious (i.e. there are more parameters to estimate) and this may cause econometric difficulties such as multicollinearity and the need for larger samples [44]. Again, the translog cost function collapses to a Cobb–Douglas cost function if the quadratic and interaction terms have statistically insignificant coefficients. A Cobb–Douglas cost function (frontier) specification is linear in natural logarithms, with panel data, it can therefore be written as:

$$ln\left(\frac{C_{it}}{P_{Dit}}\right) = \beta_0 + \beta_Y lnY_{it} + \beta_L ln\left(\frac{P_{Lit}}{P_{Dit}}\right) + \beta_K ln\left(\frac{P_{Kit}}{P_{Dit}}\right) + \beta_T d_T + \varepsilon_{it} \tag{2}$$

where i and t are the subscripts denoting the DMU and year, respectively; ln represents the natural logarithm of the earlier defined variables; and ε_{it} represents the random term that expresses the deviation of the observed cost from the optimal minimum cost defined by the efficiency frontier.

The random term $\left(\varepsilon_{it}\right)$ in Eq. 2, unlike the conventional linear regression model, has nonzero mean $\left[E(\varepsilon_{it}) > 0\right]$ and it is not normally distributed [22]. In deterministic frontier models, any deviation from the frontier is attributed to inefficiency ignoring the fact that costs can be affected by random shocks that are outside the control of the DMU. One advantage of the stochastic frontier model is its ability to recognize that deviations from the optimal minimum cost may be caused by random shocks that are outside the control of DMUs or originate from the inefficiency of the DMU. Thus, the SFA model decomposes the random term into two components $\left(\varepsilon_{it} = v_{it} + u_{it}\right)$. Thus, Eq. 2 can be rewritten as:

$$lnC_{it} = \beta_0 + \beta_Y lnY_{it} + \beta_L lnP_{Lit} + \beta_K lnP_{Kit} + \beta_T d_T + v_{it} + u_{it} \tag{3}$$

where C_{it} is the normalized total cost, lnY_{it} is the composite output, P_{Lit} is the normalized price for labor, P_{Kit} is the normalized price for capital, v_{it} is a normally distributed random component with a zero mean $\left[i.i.d.N(0, \sigma_v^2)\right]$ which represents the random shocks not manageable by the i^{th} DMU at time t, while u_{it} is the nonnegative random component $\left[E(u_{it}) \geq 0\right]$ that represents the cost inefficiency of the DMU. The cost efficiency of PHCF i at time t is defined as the ratio of the minimum cost, to the actual cost, given the same exogenous variables (i.e.lnY_{it}, P_{Lit}, and P_{Kit}). The cost efficiency of the i^{th} DMU is measured as:

$$E[\exp\left(-u_{it}\right)|\varepsilon_{it}] \tag{4}$$

where $\varepsilon_{it}\left(or u_{it} + v_{it}\right)$ is the composed error term of the model [37]. Given that the existence of the inefficiency effect is proven, the inefficiency term (u_{it}) is modeled as a parametric function of variables z_{it} that are postulated to explain the variations in the cost inefficiencies over time and/or among DMUs [22]. The inefficiency u_{it} function, in general terms, is specified as follows:

$$u_{it} = \exp\left(z_{it}\}\eta\right) \times u_i; u_i > 0 \tag{5}$$

where $z_{it} = \left(z_{1it}, \ldots, z_{Pit}\right)\prime$ is a $P \times 1$ vector of variables, which include time, that might influence inefficiency; and $\eta = \left(\eta_1, \ldots, \eta_P\right)\prime$ is a $P \times 1$ vector of parameters to be estimated. Given that the two-step procedure where inefficiency scores already estimated are regressed on a vector of exogenous variables z_i has long been recognized as biased [37], this study adopts the single-step procedure which accounts for the exogenous influences on inefficiency by parameterizing the distribution function of the u_i as a function of z_i. If u_i follows a truncated-normal distribution, that is, $u_i \sim N^+(0, u_i^2)$, then the parameterization function given in Eq. 5 is well suited [45].

In studying the cost efficiency analysis, we are interested in identifying the impact of changes in the volume of primary healthcare services on the cost of delivering such services. Thus, the study measures the scale of economies of both HCs and CHPS compounds in Ghana. A significant proportion of the total assets of PHCFs are fixed assets in the form of buildings, vehicles, equipment, and furniture. This makes PHCFs largely fixed-cost operations, and those that provide more PHC services are able to spread their fixed costs across a wider activity base thereby reducing the average cost per PHC service. Following Berger et al. [46], economies of scale are estimated as the proportionate rise in costs resulting from a proportional increase in output. From Eq. 3, the scale of economies (SE) is computed as:

$$SE = \frac{\partial lnC}{\partial lnY} \tag{6}$$

Since the Cobb–Douglas model in Eq. 2 is logged in all variables, the derivative in Eq. 6 is an estimate of the cost elasticity to output. In Eq. 6, the scale efficiency (SE) value less than 1 indicates economies of scale which means that increases in costs are smaller than the proportional output increases. Scale efficiency (SE) value greater than 1 represents diseconomies of scale.

3.4 Definition of variables

Available data for any given year for each facility includes total expenditure, employees' compensations, expenditure on drugs and other supplies, number of beds, total number of employees, catchment population, and number of outpatient visits, outreach visits, and deliveries. Since the study is measuring efficiency in a cost functional framework, total operating costs [represented as *costs* (TC) in the model] is used as the dependent variable. The total costs are made up of employee compensations, service expenses, and capital costs. The service expenses include costs such as drugs and vaccines costs, material and consumables costs, and travel and transportation expenses. The capital costs are computed as the residual costs after deducting employees' compensations and service expenses. The capital costs are mainly related to purchase of furniture, computer and accessories, tools and test equipment, motor bikes and bicycles, and expenses on maintenance and repairs. Accordingly, we include three input prices in our cost function, viz, wage [represented as *labour input price* $\left(P_L\right)$], *capital input price* $\left(P_K\right)$, and *service input price* $\left(P_S\right)$. We also included a trend variable d_T.

Following previous empirical studies [47–49], total number of beds in the facility is used as a proxy for capital stock. Thus, the capital input price $\left(P_{Kit}\right)$ is calculated as total capital costs divided by the number of beds. Labor input price (P_L) was computed as the total employees' compensations divided by the total number of employees at the facility, while the service input price $\left(P_S\right)$ was computed as the total service expenditure (i.e. expenditure on drugs and other supplies) divided by a total number of services rendered. All costs and prices were adjusted for inflation using Ghana's Consumer Price Index (CPI) and were measured in 2011 Ghana cedis.

In measuring output in health, the ideal variable is an increment in patient health status from the healthcare received at the health facility. However, since it is technically difficult to measure that health output, in all health efficiency studies, intermediate outputs are used in their place [49]. Most parametric studies on efficiency in healthcare take into account only the number of outpatients and/or inpatients as intermediate output variables [50–52]. However, most aspects of the activities of a typical PHCF are preventive healthcare services as well as curative healthcare services. In order to reflect the true multi-output nature of PHCFs, we include three major aspects of primary healthcare variables, viz: *curative services* (i.e. outpatient visits and assisted child-birth deliveries), *preventive services* (such as immunizations, family planning, antenatal, postnatal, and reproductive consultations), and *outreach visits* (which is the sum of outreach and home visits). These multiple outputs were merged into one aggregated output index. This approach has the advantages of maximizing the degrees of freedom for the estimation and minimizing collinearity problems given the limited number of observations. The only disadvantage is that it breakdowns the multidimensional output vector into an aggregated output index [52].

Two different sets of variables are required to estimate the stochastic cost frontier model, viz: the variables in the stochastic frontier model (i.e.Y, P_L, P_K, P_D, d_T) and the z_{it} variables in the inefficiency model. Table 1 presents the definitions of the variables used in this study.

With regards to the parametric part of the inefficiency component, we consider four environmental variables z_{it} which have the potential to explain the variability of cost inefficiencies among PHCFs. These are the medical staff to catchment population ratio (MSD); the ratio of revenue from the National Health Insurance Scheme ($NHIS$) as reimbursement for patients with NHIS card to the total revenue; the facility size which is proxied by the number of inpatient beds in the facility ($SIZE$); and the age of the facility measured as the number of years the facility has been in existence (AGE). The choice of these variables was guided by healthcare literature and available data.

Economic theory suggests that economies of scale (or diseconomies of scale) can affect the cost efficiency of primary healthcare services in a PHCF as the facility size changes [53]. The most commonly used measure of facility

Table 1 Variables and their definitions

Variable	Description
Variables for the cost stochastic frontier model	
Total cost (C_{it})	Annual total costs include employee compensations, material and consumables, travel and transportation, drugs and vaccine, and minor repairs and maintenance costs. It was measured in cedis (Ghana currency)
Labor input price (P_{Lit})	Labor price is measured by the ratio of total employees' compensations to the number of employees. It was measured in cedis (Ghana currency)
Capital input price (P_{Kit})	The ratio of total capital costs to the number of inpatient beds in the facility. It was measured in cedis (Ghana currency)
Service input price (P_{Sit})	Service price per unit is measured as the ratio of total service expenses to total output. It was measured in cedis (Ghana currency)
Total output (Y_{it})	The linear aggregation of three major PHC activities within a given year: *curative services* (sum of outpatient visits and live birth deliveries), *preventive services* (sum of postnatal family planning, immunizations, reproductive, and antenatal consultations), and *outreach visits*
Time d_T	Trend variable
Variables for the inefficiency model (z_{it})	
Medical staff density (MSD)	The number of medical staff (measured as the sum of Physician Assistants, Nurses, and other medical personnel such as lab technicians and pharmacists) per 1000 catchment population. Measured per 1000 people
NHIS revenue ($NHIS$)	The ratio of revenue from NHIS to the total revenues. Total revenue is the sum of all sources revenue to the facility (including NHIS, out-of-pocket payment, reimbursements for private insurance scheme subscribers, etc.). It was measured in cedis (Ghana currency)
Size of facility ($SIZE$)	Proxied by the number of beds in the facility. Measured in units of beds
Age of facility (AGE)	The number of years the facility has been in existence. Measured in years

NHIS National Health Insurance Scheme

size in the literature is the number of beds in the facility [54–56]. In this study, we use the number of beds as a proxy for facility size. However, the literature presents mixed results on the effect of size on efficiency. While some studies show that small-sized healthcare facilities are more efficient than large ones [54], others show the opposite [56]. Moreover, the effect of facility size on cost efficiency is expected to depend on facility-specific factors such as managerial competence. In particular, the size of the hospital may decrease inefficiency due to economies of scale, but increase inefficiency due to poor management practices.

The density of medical staff, measured as the number of medical staff per 1000 catchment population of a PHCF, is expected to affect efficiency. A lower staff density can result in longer waiting times for both curative and preventive primary healthcare services. This can hinder not only early detection and treatment of illnesses, leading to increased costs, but it can also discourage people from seeking medical attention when needed [50]. Therefore, a lower staff density is expected to have a detrimental impact on cost efficiency.

Empirical health economics theory suggests that medical health insurance coverage may lead to inefficiencies in the production of health due to ex-ante and ex-post moral hazard effects [57]. Ex-ante moral hazard effects arise from insurance coverage and can result in a lax approach to preventive measures such as a healthy lifestyle, preventive care, and early detection of diseases prior to the onset of sickness. On the other hand, ex-post moral hazard effects lead to increased treatment costs, including longer hospital stays and unnecessary visits to healthcare providers induced by health insurance [58]. Therefore, a higher ratio of revenue from the National Health Insurance Scheme (NHIS) to total revenue is expected to be associated with lower cost efficiency of primary healthcare services production.

It is anticipated that the age of a PHCF would positively affect its cost efficiency. Facilities that have been in operation for many years are likely to have well-established medical protocols and procedures that can expedite patient recovery while also reducing medical errors and fostering a culture of safety. Medical errors are a major contributor to healthcare costs, including individual health expenses [59].

4 Results and discussions

4.1 Descriptive statistics

Table 2 provides a summary of the descriptive statistics of the primary variables used in the inefficiency analyses and stochastic frontier analysis (SFA) for the two major types of primary healthcare facilities (PHCFs) in Ghana, namely Health Centers (HCs) and Community-Based Health Planning and Services compounds (CHPSs).

On average, HCs provide 4247 primary healthcare services at an annual cost of GHS 121,505, covering a catchment population of 1295 per medical staff. Conversely, CHPSs spend an average of GHS 37,914 annually to deliver 1246 primary healthcare services to a catchment population-to-medical staff ratio of 1319. The large difference of the average annual cost between HCs and CHPS facilities can be attributed in part to the high level of volunteerism within the CHPS system. The CHPS system typically comprises community health nurses (CHN), community health volunteers (CHV) and the community health management teams (CHMT). The CHV and CHMT are all volunteer positions. Despite being unpaid, their contribution is essential for the efficient operation of CHPS compounds, as they play pivotal roles in both the community's healthcare demand and supply sides.

The average cost per primary healthcare service is GHS 28.6 and GHS 30.4 for HCs and CHPSs, respectively. Interestingly, despite HCs producing a greater average output, their cost per unit of output is lower than that of CHPSs, indicating the presence of economies of scale in primary healthcare service production. Additionally, HCs have a higher labor price but lower capital and service prices relative to CHPSs.

4.2 Cobb–Douglas cost frontier estimation results

Table 3 displays the findings of the estimation of Cobb–Douglas cost functions for HCs and CHPS, utilizing distinct frontiers. The model estimates the coefficients for output, labor price, capital price, and trend variables at their initial levels, assuming different isocost technologies for each type of PHCF. The outcomes demonstrate that both categories of PHCFs have positive and statistically significant coefficients.

Since the coefficients are computed from the log–log model, they can respectively be interpreted as output, labor price, and capital price elasticities of cost. The estimated coefficients of the variables have the expected signs since both price elasticities and the output elasticity of cost are positive. These meet the a priori expectation of cost minimization. From the reported results in Table 3 cost is nondecreasing in prices and monotonic in output.

The cost elasticity with respect to output equals 0.143 for HCs and 0.195 for CHPSs. This implies the presence of economies of scale for both classes of PHCFs. This means that a proportionate increase in PHC services leads to a lower proportionate increase in cost for all PHCFs. However, the effect differs between the two main classes of PHCFs, which

Table 2 Descriptive statistics

Variable	HCs (195 observations)				CHPS (233 observations)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
SFA model								
Total costs (TC)	121,505	80,449.1	11,524.3	434,167	37,914.2	31,034.3	6410.5	257,557
Labor price (P_L)	6464.1	4619.5	771.4	24,551.4	3674.8	3128.9	204.2	15,440.5
Capital price (P_K)	1398.99	2243.8	11.6	22,050.7	1686.8	9966.2	0.124	150,000
Service price (P_S)	6.066	16.3	0.144	167.667	10.3	40.9	0.029	432.7
Total output (Y)	4246.6	4023.8	7	23,700	1245.8	1318.3	5	7273
Trend (t)	3	1.418	1	5	3.25	1.365	1	5
Inefficiency model								
Medical staff density	0.772	0.824	0.041	5.11	0.758	0.555	0.043	2.53
NHIS share	0.624	0.343	0	1	0.622	0.345	0	1
Facility (beds) size	5.872	4.1	0	15	1.7	2.0	0	6
Facility age (in years)	21.59	15.6	5	65	7.4	5.5	2	29

All monetary values were adjusted for inflation using Ghana's Consumer Price Index (CPI) and were measured in 2011 Ghana cedis (GHS). In 2011, GHS 1 = USD 1.6395

Table 3 Maximum likelihood estimated parameters of the Cobb–Douglas cost frontier model with inefficiency component

	HC Coefficient	CHPS Coefficient
Cost frontier		
lnY	0.143*** (0.051)	0.195*** (0.029)
lnP_L	0.776*** (0.028)	0.741*** (0.023)
lnP_K	0.085*** (0.028)	0.112*** (0.021)
$Trend$	0.077*** (0.014)	0.056*** (0.013)
$Constant$	11.361*** (0.105)	10.295*** (0.078)
$Inefficiencyeffect$		
$Facility\_age$	−0.372*** (0.137)	0.150 (0.132)
$Facility\_size$	−0.198* (0.117)	0.582** (0.236)
$NHIS\_share$	1.299 (1.042)	−0.503 (2.280)
$Medstaff\_density$	−10.674***(3.036)	3.720** (1.590)
$Constant$	4.150* (2.160)	−10.956** (4.783)
$Varianceparameters$		
$Sigma\left(\sigma_v^2+\sigma_u^2\right)^{\frac{1}{2}}$	0.207***(0.011)	4.617***(1.299)
$Lamda(\lambda=\sigma_u/\sigma_v)$	0.514***(0.039)	32.455***(1.320)
$WaldChi^2$	2061.9***(0.000)	4824.5***(0.000)
$Logsimulated\_Likelihood$	−9.41	−38.93
$Observations$	195	233

Standard errors are shown in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively

is an evidence in support of the existence of heterogeneity in production technology for the provision of PHC services between the two categories of PHCFs.

The homogeneity in prices for both groups is tested instead of imposing it. The results show that the homogeneity in prices is statistically significant for the two classes of PHC providers in Ghana. The significant difference in the input prices among the groups is evidence of the existence of heterogeneity in production technology between HCs and CHPSs. It is observed that HCs have higher elasticity of labor relative to CHPSs while the opposite exist in terms of the elasticity of capital.

As indicated by the trend variable, costs for providing PHC services increase with time. The coefficients on the trend variable for HCs (0.077) and CHPSs (0.056) implies that total cost for providing primary healthcare services increased in real terms by 7.7% for HCs and 5.6% for CHPSs per annum on average across the PHCFs over the period of study. Having set up the Cobb–Douglas model and checked that the model is consistent with theory, we now turn to the estimation of the cost efficiency scores.

4.3 Cost efficiency scores

We estimated the cost efficiency in Eq. 3 using the Battese and Coelli's [36] method and generated the cost efficiency scores as described in Eq. 4. The cost efficiency scores were estimated for HCs and CHPS, with different frontiers. Thus, no comparison is made between the scores obtained. Table 4 presents descriptive statistics of the estimated cost efficiency for each year for both the HCs and CHPS. Cost efficiency is defined as the ratio of the optimal minimum cost to the actual cost. It takes values between 0 and 1. More efficient PHCFs have values closer to 1. The mean cost efficiency for HCs and CHPS are estimated at 0.616 and 0.858, respectively, implying that given the output levels, on average, the minimum cost at which HCs and CHPS provide PHC services is about 61.6% and 85.8%, respectively. Alternatively, if HCs and CHPS were to use their resources as efficiently as possible, they could reduce their production costs by roughly 38.4% and 14.2%, respectively.

Table 4 presents the levels of cost efficiency for the entire sample and for different size classes for both HCs and CHPS from 2007 to 2011. For both HCs and CHPS, large facilities have higher cost efficiency than small facilities. These findings are in line with those obtained by Mahate et al. [55] and Watcharasriroj and Tang [59] who found that large hospitals are more efficient than small-sized ones. It is also observed that the cost-efficiency performance of

Table 4 Cost Efficiency by Type and Size of Primary Healthcare Facilities over Years

	Health Centres (HCs)			CHPS Compounds		
Year	Full Sample	Small HCs	Large HCs	Full Sample	Small CHPS	Large CHPS
2007	0.676	0.609	0.761	0.810	0.808	0.813
2008	0.670	0.625	0.718	0.860	0.857	0.864
2009	0.625	0.562	0.696	0.871	0.849	0.902
2010	0.590	0.534	0.659	0.849	0.841	0.859
2011	0.556	0.497	0.629	0.881	0.863	0.903
Average	**0.616**	**0.557**	**0.685**	**0.858**	**0.846**	**0.874**

Large HCs (CHPS) are HCs (CHPS) with inpatient beds greater than 5 (2), and small HCs (CHPS) are HCs (CHPS) with 5 (2) or fewer inpatient beds

CHPS has been improving over the study period, with the exception of the year 2010 when the performance dipped. However, the cost-efficiency level of HCs has been declining over the study period.

We further categorize each type of PHCFs into three groups based on their locations—rural, semi/peri-urban, and urban—and computed the mean average cost efficiency for each group. A one-way ANOVA tests performed for both HCs and CHPS showed significant differences at $p < 0.05$ level for the three locations with the results of $[F(2, 157) = 5.65, p = 0.0043]$ for the HCs and $[F(2, 223) = 3.47, p = 0.0328]$ for CHPS. Figure 3 shows that among the HCs, those located in semi-/peri-urban areas have the highest cost efficiency relative to those located in urban and rural areas. However, among the CHPS, those located in urban areas are most cost-efficient compared to those in semi-/peri-urban and rural areas.

Figure 4 plots the average cost efficiency scores of HCs and CHPS on choropleth maps in panels A and B, respectively. Here, it can be seen that HCs in the regions like Brong-Ahafo and Western performed best. They were followed by regions like Ashanti and Central. For the cost-efficiency performance in the provision of PHC services at the level of CHPS, Northern and Western regions registered the highest scores, followed by Volta and Ashanti Regions. The average cost efficiency scores for each region for both HCs and CHPS are presented in Additional file 1: Appendices S2 and S3, respectively. The ANOVA test results of the significance in the differences of scores across the regions for both HCs and CHPS are also presented in Additional file 1: Appendices S4 and S5, respectively.

Panel B of Fig. 4 shows the distribution of cost efficiency of HCs and CHPS in Ghana. With regards to the performance of HCs, the most cost-efficient regions are Brong-Ahafo and Western while the Northern and Western regions emerged as the best cost-efficient regions in the provision of PHC services at the level of CHPS compounds.

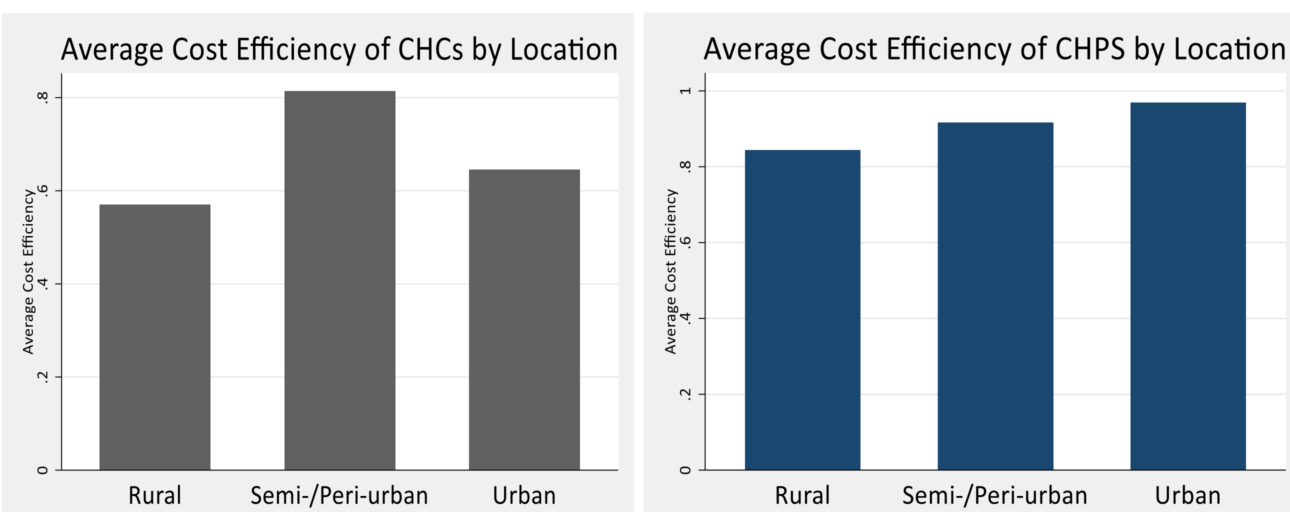


Fig. 3 Average cost efficiency of HCs and CHPS by locations

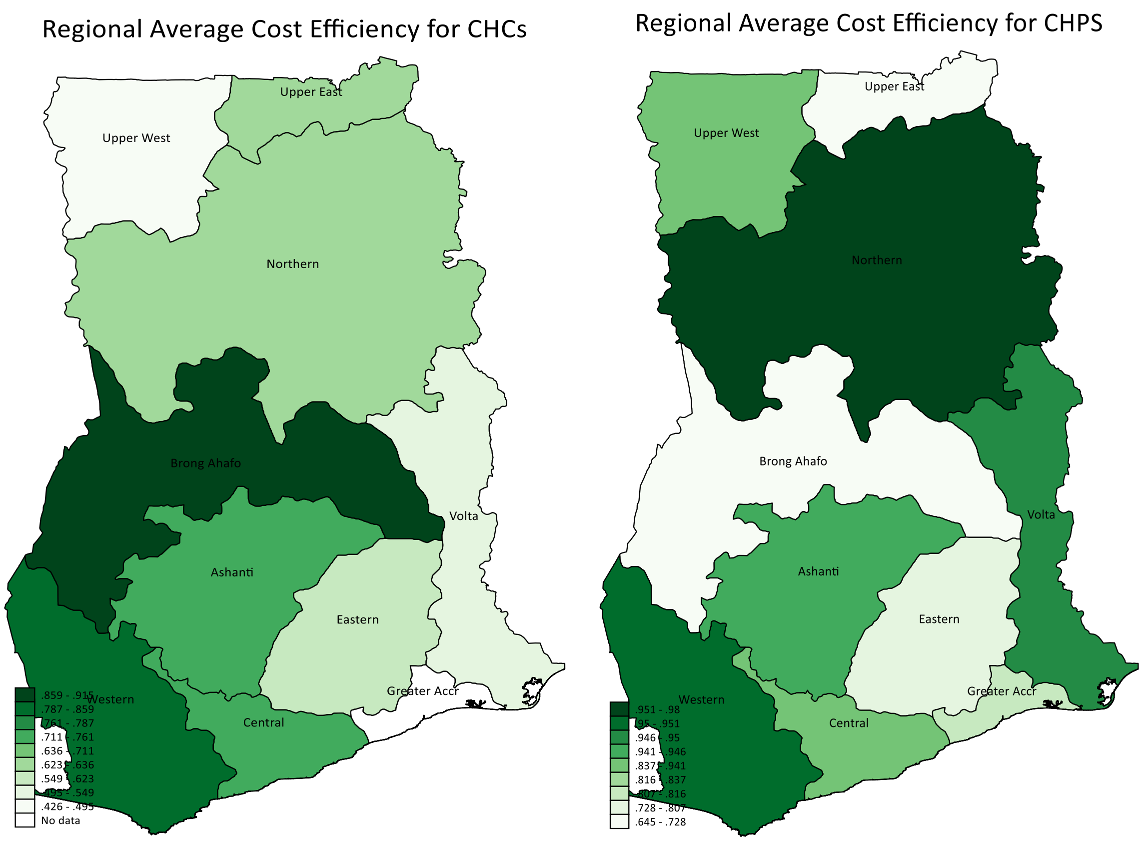


Fig. 4 Choropleth maps showing regional cost efficiency of HCs and CHPS in Ghana

4.4 Determinants of cost efficiency

In general, the differences in the cost efficiency scores of the sampled PHCFs could be explained by some facility-specific characteristics. Facility age, size, location, medical staff density, service quality, and socio-economic factors are common explanatory variables used in previous empirical studies. In this study, facility age (*Facility_age*), facility size (*Facility_size*), share of NHIS revenue to the total revenue (*NHIS_share*), and medical staff density (*Medstaff_density*) are included in the inefficiency effect model estimation. Some other explanatory variables were excluded from this second-stage analysis partly due to collinearity problems (e.g. cash-and-carry revenue as a share of total revenue), data unavailability (e.g. service quality), and statistically insignificant results (e.g. catchment population). The results of the truncated regression are also presented in Table 3. The dependent variable used in the truncated regression is the estimated cost inefficiency scores (i.e. $1 - \widehat{\theta} < 1$). Hence, a negative (positive) coefficient means that an increase in the related explanatory variable leads to an increase (decrease) in the cost efficiency of the primary healthcare facility. The results show that the effects of these covariates differ across the two classes (i.e. HCs and CHPSs) of primary healthcare facilities.

Referring to the results in the second part of Table 3, facility age is found to be negatively associated with cost inefficiency for HCs, which suggests that HCs experience the learning curve theory. That is, as compared to CHPS, the provision of PHC services by HCs over the years translates into lower cost and/or higher output as a result of improved performance of the workforce. This result is consistent with those obtained in earlier empirical studies, such as those obtained by Rodziewicz et al. [59] who found that healthcare facilities with many years in practice and have well established medical procedures and protocols speed up patients' recoveries, reduce iatrogenic exposures, and ultimately contribute to substantial reduction in healthcare costs. Therefore, HCs with many years in practice provide PHC services at relatively lower cost efficiency levels.

The size of a PHC facility is measured by the number of inpatient beds. The size variable is included in the analysis to assess its effect on cost efficiency performance. The coefficient of the facility size is estimated and indicates a negative association with cost inefficiency for HCs but a positive association with cost inefficiency for CHPSs. These results suggest that while increasing the size of HCs would significantly reduce cost inefficiency, doing the same with CHPSs would worsen their cost-efficiency performance. These findings are in line with those obtained by Mahate et al. [56] and Watcharasriroj and Tang [60] who found that large hospitals are more efficient than small-sized ones. In Ghana, HCs are on average four times larger in size relative to CHPS compounds in terms of both catchment population and inpatient beds [25].

Medical staff density which is measured as the number of medical staff per thousand catchment population is included in the analysis. The estimated medical staff density coefficient is negative for HCs but positive for CHPS, which indicates that HCs (CHPS) with higher medical staff to patients ratio are likely to be more cost efficient (inefficient) than those with lower ratios. In Ghana, HCs which are mostly located in peri-urban or semi-urban areas suffer from long queues and longer waiting times which does not only prevent early detection and treatment of ailments to enhance full recovery at lower cost but also discourage people from seeking the needed primary healthcare services. Thus, improving the medical staff to patients ratio at the level of HCs go a long way to reduce cost inefficiency. However, CHPS which are mostly located in villages and hamlets experience no such long queues and longer waiting times, therefore, increasing the medical staff to patients ratio would rather increase cost inefficiency. These results are consistent with those obtained by Cylus et al. [50].

4.5 Strengths and limitations of the study

This study suffers from some limitations, which include the dated nature of the dataset and the limited number of data points used. The data employed for the analysis in this study was gathered more than a decade ago. We, therefore, caution readers about it while interpreting the results within the present context. However, the study has several strengths and offers valuable empirical insights that can aid policy-makers in shaping Primary Health Care (PHC) policies.

5 Conclusion and policy implications

This paper evaluates the cost efficiency and its determinants of 102 primary health care facilities (PHCFs), made up of 43 Health Centres (HCs) and 59 Community-Based Health Planning and Services (CHPS) compounds in Ghana over the period of 2007–2011. This study is one of the first to estimate the cost efficiency of PHCFs in Ghana. The study finds heterogeneity in the cost efficiency scores which explains the fact that these PHC facilities are not homogeneous and do not have the same productive capacity. Overall, the findings show that on average, the selected HCs and CHPS compounds obtained cost efficiency score of 61.6% and 85.8%, respectively. The study also revealed that facility size, medical staff density, and facility age are the main factors that explain the heterogeneity in cost efficiency among PHCFs.

The results have valuable policy implications for improving the delivery of PHC services in Ghana. The results of the study revealed that increasing the number of medical staff and the size of health center facilities improves their cost efficiency. However, it is important to note that implementing these measures have adverse effects on the cost efficiency of CHPS compounds. In this regard, we infer that incentive packages designed to attract medical personnel, such as physician assistants, midwives, and nurses to underserved communities would improve the cost efficiency performance in the provision of PHC services.

Another practical implication is that policy makers must address issues related to the size of health centres, in terms of number of inpatient beds, particularly those in densely populated areas to enhance their cost efficiency performance. The results further indicate that for Ghana to attain the UHC goal by the year 2030, policy makers must address most of the bottlenecks that impede accessibility to PHC services. We recommend to Ghana Health Service to consider leveraging on the modern technology in the provision of healthcare services such as telehealth and telemedicine to enhance access to PHC services for people living in hard-to-reach and densely populated communities. Future studies must qualitatively delve into the physical, financial, and cultural barriers that impede access to PHC services.

Author contributions Kwadwo Arhin and Jacob Novignon conceived the presented idea. Kwadwo Arhin and Eric Fosu Oteng-Abayie developed the theory and performed the computations. Kwadwo Arhin wrote the manuscript with support from Eric Fosu Oteng-Abayie and Jacob Novignon. Eric Fosu Oteng-Abayie and Jacob Novignon verified the analytical methods and supervised the findings of the work. All authors discussed the results and contributed to the drafting of the manuscript.

Funding No external funding was received. It was funded by the author himself.

Data availability The dataset used in this study was extracted from the database of the Institute of Health Metrics and Evaluation (IHME). The data is publicly available. The data can be accessed at: http://ghdx.healthdata.org/record/ghana-access-bottlenecks-costs-and-equity-project-2012/.

Declarations

Ethics approval and consent to participate Not applicable.

Competing interests We declare no competing interests.

References

1. Gizaw Z, Astale T, Kassie GM. What improves access to primary healthcare services in rural communities? A systematic review. BMC Primary Care. 2022. https://doi.org/10.1186/s12875-022-01919-0.
2. Arhin K, Frimpong AO, Acheampong K. Effect of primary health care expenditure on universal health coverage: evidence from sub-Saharan Africa. Clin Econ Outcomes Res. 2022;14:643–52. https://doi.org/10.2147/ceor.s380900.
3. Doherty JE, Govender R. The cost-effectiveness of primary care services in developing countries: a review of the international literature. Med Polit Sci. 2004;200:53–68.
4. Rao M, Pilot E. The missing link—the role of primary care in global health. Glob Health Action. 2014;7(1):23693. https://doi.org/10.3402/gha.v7.23693.
5. Sacks E, Schleiff M, Were M, Chowdhury AM, Perry HB. Communities, universal health coverage and primary health care. Bull World Health Organ. 2020;98(11):773–80. https://doi.org/10.2471/blt.20.252445.
6. Kruk ME, Porignon D, Rockers PC, Van Lerberghe W. The contribution of primary care to health and health systems in low- and middle-income countries: a critical review of major primary care initiatives. Soc Sci Med. 2010;70(6):904–11. https://doi.org/10.1016/j.socscimed.2009.11.025.
7. Perry HB, Rassekh BM, Gupta S, Wilhelm J, Freeman PA. Comprehensive review of the evidence regarding the effectiveness of community–based primary health care in improving maternal, neonatal and child health: 1. Rationale, methods and database description. J Glob Health. 2017. https://doi.org/10.7189/jogh.07.010901.
8. Starfield B. Primary care: an increasingly important contributor to effectiveness, equity, and efficiency of health services. SESPAS report 2012. Gac Sanit. 2012;26:20–6. https://doi.org/10.1016/j.gaceta.2011.10.009.
9. Friedberg MW, Hussey PS, Schneider EC. Primary care: a critical review of the evidence on quality and costs of health care. Health Aff. 2010;29(5):766–72. https://doi.org/10.1377/hlthaff.2010.0025.
10. Ghana Statistical Service (GSS) and ICF. Ghana Demographic and Health Survey 2022: Key Indicators Report. Accra, Ghana, and Rockville, Maryland, USA: GSS and ICF; 2023. https://dhsprogram.com/pubs/pdf/PR149/PR149.pdf
11. Adu J, Mulay S, Owusu MF. Reducing maternal and child mortality in rural Ghana. Pan Afr Med J. 2021. https://doi.org/10.11604/pamj.2021.39.263.30593.
12. Osei D, d'Almeida S, George MO, Kirigia JM, Mensah AO, Kainyu LH. Technical efficiency of public district hospitals and health centres in Ghana: a pilot study. Cost Eff Resour Alloc. 2005. https://doi.org/10.1186/1478-7547-3-9.
13. Marschall P, Flessa S. Efficiency of primary care in rural Burkina Faso. A two-stage DEA analysis. Health Econ Rev. 2011. https://doi.org/10.1186/2191-1991-1-5.
14. Saronga HP, Duysburgh E, Massawe S, et al. Efficiency of antenatal care and childbirth services in selected primary health care facilities in rural Tanzania: a cross-sectional study. BMC Health Serv Res. 2014. https://doi.org/10.1186/1472-6963-14-96.
15. Novignon J, Nonvignon J. Improving primary health care facility performance in Ghana: efficiency analysis and fiscal space implications. BMC Health Serv Res. 2017. https://doi.org/10.1186/s12913-017-2347-4.
16. Akazili J, Adjuik M, Jehu-Appiah C, Zere E. Using data envelopment analysis to measure the extent of technical efficiency of public health centres in Ghana. BMC Int Health Hum Rights. 2008. https://doi.org/10.1186/1472-698x-8-11.
17. Alhassan RK, Nketiah-Amponsah E, Akazili J, Spieker N, Arhinful DK, Rinke de Wit TF. Efficiency of private and public primary health facilities accredited by the National Health Insurance Authority in Ghana. Cost Eff Resour Alloc. 2015. https://doi.org/10.1186/s12962-015-0050-z.
18. Kirirgia JM, Sambo LG, Scheel H. Technical efficiency of public clinics in Kwazulu- Natal Province of South Africa. East Afr Med J. 2001. https://doi.org/10.4314/eamj.v78i3.9070.
19. Kirigia JM, Emrouznejad A, Sambo LG, Munguti N, Liambila W. Using data envelopment analysis to measure the technical efficiency of public health centers in Kenya. J Med Syst. 2004;28(2):155–66. https://doi.org/10.1023/b:joms.0000023298.31972.c9.
20. Renner A, Kirigia JM, Zere EA, et al. Technical efficiency of peripheral health units in Pujehun district of Sierra Leone: a DEA application. BMC Health Serv Res. 2005. https://doi.org/10.1186/1472-6963-5-77.

21. Bobo FT, Woldie M, Wordofa MA, et al. Technical efficiency of public health centers in three districts in Ethiopia: two-stage data envelopment analysis. BMC Res Notes. 2018. https://doi.org/10.1186/s13104-018-3580-6.
22. Kumbhakar SC, Wang HJ, Horncastle A. A practitioner's guide to stochastic frontier analysis using stata. Cambridge University Press; 2015. https://doi.org/10.1017/cbo9781139342070.
23. Awoonor-Williams JK, Tindana P, Dalinjong PA, Nartey H, Akazili J. Does the operations of the National Health Insurance Scheme (NHIS) in Ghana align with the goals of Primary Health Care? Perspectives of key stakeholders in northern Ghana. BMC Int Health Hum Rights. 2016. https://doi.org/10.1186/s12914-016-0096-9.
24. Bishai D, Schleiff M. Achieving health for all: primary health care in action. JHU Press; 2020.
25. Nyonator FK, Awoonor-Williams JK, Phillips JF, Jones TC, Miller RA. The Ghana Community-based Health Planning and Services Initiative for scaling up service delivery innovation. Health Policy Plan. 2005;20(1):25–34. https://doi.org/10.1093/heapol/czi003.
26. Egan KF, Devlin K, Pandit-Rajani T. Community health systems catalog country profile: Ghana. Arlington: Advancing Partners & Communities; 2017.
27. Seddoh A, Adjei A, Nazzar A. Ghana's National health insurance scheme: views on progress, observations and commentary. Accra: Centre for Health and Social Services; 2011.
28. Ward WB, Neumann AK, Pappoe ME. Community health education in rural Ghana: the Danfa project—an assessment of accomplishments. Int Q Community Health Educ. 1981;2(2):143–55. https://doi.org/10.2190/q5l9-k74b-8up6-mqmd.
29. Toves K. Supporting country-led primary health care measurement in Ghana. Results for Development. Published December 12; 2019. https://r4d.org/blog/supporting-country-led-primary-health-care-measurement-in-ghana. Accessed 8 May 2021.
30. Kweku M, Amu H, Awolu A, et al. Community-based health planning and services plus programme in Ghana: a qualitative study with stakeholders in two systems learning districts on improving the implementation of primary health care. PLoS ONE. 2020;15(1): e0226808. https://doi.org/10.1371/journal.pone.0226808.
31. Institute of Health Metrics. Data release information sheet. Washington, D.C.: Institute of Health Metrics; 2015.
32. Aigner D, Lovell CK, Schmidt P. Formulation and estimation of stochastic frontier production function models. J Econometr. 1977;6(1):21–37. https://doi.org/10.1016/0304-4076(77)90052-5.
33. Meeusen W, van Den Broeck J. Efficiency estimation from Cobb-Douglas production functions with composed error. Int Econ Rev. 1977;18(2):435. https://doi.org/10.2307/2525757.
34. Gold SC. Modeling short-run cost and production functions in computerized business simulations. Simul Gaming. 1992;23(4):417–30. https://doi.org/10.1177/1046878192234003.
35. Pitt MM, Lee LF. The measurement and sources of technical inefficiency in the Indonesian weaving industry. J Dev Econ. 1981;9(1):43–64. https://doi.org/10.1016/0304-3878(81)90004-3.
36. Kumbhakar SC, Lovell CAK. Stochastic frontier analysis. Cambridge University Press; 2000. https://doi.org/10.1017/cbo9781139174411.
37. Battese GE, Coelli TJ. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir Econ. 1995;20(2):325–32. https://doi.org/10.1007/bf01205442.
38. Parmeter CF, Kumbhakar S. Efficiency analysis: a primer on recent advances (foundations and trends(R) in econometrics). Now Publishers; 2014.
39. Park BU, Simar L, Zelenyuk V. Categorical data in local maximum likelihood: theory and applications to productivity analysis. J Prod Anal. 2014;43(2):199–214. https://doi.org/10.1007/s11123-014-0394-y.
40. Sengupta JK. Estimating efficiency by cost frontiers: a comparison of parametric and nonparametric methods. Appl Econ Lett. 1995;2(4):86–90. https://doi.org/10.1080/758529808.
41. Hall RE. The specification of technology with several kinds of output. J Polit Econ. 1973;81(4):878–92. https://doi.org/10.1086/260086.
42. Jehle GA, Reny PJ. Advanced microeconomic theory. Financial Times/Prentice Hall; 2011.
43. Coelli T, Battese GE, O'donnell CJ, Prasada Rao DS. An introduction to efficiency and productivity analysis. Springer Science+Business Media, Inc; 2005.
44. Leite D, Pessanha J, Simões P, Calili R, Souza R. A stochastic frontier model for definition of non-technical loss targets. Energies. 2020;13(12):3227. https://doi.org/10.3390/en13123227.
45. Wang H, Schmidt P. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. J Prod Anal. 2002;18(2):129–44. https://doi.org/10.1023/a:1016565719882.
46. Berger AN, Hanweck GA, Humphrey DB. Competitive viability in banking: scale, scope, and product mix economies. J Monet Econ. 1987;20(3):501–20. https://doi.org/10.1016/0304-3932(87)90039-0.
47. Ravaghi H, Alidoost S, Mannion R, Bélorgeot VD. Models and methods for determining the optimal number of beds in hospitals and regions: a systematic scoping review. BMC Health Serv Res. 2020. https://doi.org/10.1186/s12913-020-5023-z.
48. Blades D, Meyer-Zu-Schlochtern J. How should capital be represented in studies of total factor productivity how should capital be represented in studies of total factor productivity? 1997. https://www.oecd.org/sdd/na/2666902.pdf
49. Growiec J, McAdam P, Muck J. Endogenous labor share cycles: theory and evidence. SSRN Electr J. 2015. https://doi.org/10.2139/ssrn.2578961.
50. Cylus J, Papanicolas I, Smith PC. Health system efficiency: how to make measurement matter for policy and management. In: Health Policy Series. 46 European Observatory on Health Systems and Policies. Brussels, Belgium; 2016. ISBN: 9789289050418.
51. Serván-Mori E, Heredia-Pi I, García DC, et al. Assessing the continuum of care for maternal health in Mexico, 1994–2018. Bull World Health Organ. 2020;99(3):190–200. https://doi.org/10.2471/blt.20.252544.
52. Newhouse JP. Commentary on Getzen's "aggregation and the measurement of health care costs." Health Serv Res. 2006;41(5):1955–8. https://doi.org/10.1111/j.1475-6773.2006.00559.x.
53. Carey K, Burgess JF, Young GJ. Economies of scale and scope: the case of specialty hospitals. Contemp Econ Policy. 2014;33(1):104–17. https://doi.org/10.1111/coep.12062.
54. Atake EH. Analysis of the technical efficiency of public hospitals in Togo: a non-parametric approach. AERC Research Paper 357; African Economic Research Consortium; 2019.

55. See KF, Yen SH. Does happiness matter to health system efficiency? A performance analysis. Health Econ Rev. 2018. https://doi.org/10.1186/s13561-018-0214-6.
56. Mahate A, Hamidi S, Akinci F. Measuring the effect of size on technical efficiency of the United Arab Emirates hospitals. Global J Health Sci. 2016;9(3):116. https://doi.org/10.5539/gjhs.v9n3p116.
57. Zweifel P, Frech HE. Health economics. Springer Science & Business Media; 2012.
58. Bates LJ, Mukherjee K, Santerre RE. Medical insurance coverage and health production efficiency. J Risk Insurance. 2010;77(1):211–29. https://doi.org/10.1111/j.1539-6975.2009.01336.x.
59. Rodziewicz TL, Houseman B, Hipskind JE. Medical error reduction and prevention. StatPearls, Treasure: StatPearls Publishing; 2023. https://www.ncbi.nlm.nih.gov/books/NBK499956
60. Watcharasriroj B, Tang JCS. The effects of size and information technology on hospital efficiency. J High Technol Manag Res. 2004;15(1):1–16. https://doi.org/10.1016/j.hitech.2003.09.001.