Examining Drivers of Technical, Allocative and Economic Efficiencies in Cocoa Farming: Empirical Evidence from Ghana.

Emmanuel W. Inkoom

emmanuel.inkoom@ucc.edu.gh / inkowis@gmail.com

Henry D. Acquah

Samuel K. N. Dadzie

(corresponding author)

sdadzie@ucc.edu.gh

DOI//http://dx.doi.org/10.4314/gjds.v19i2.1

Abstract

In Ghana, cocoa production is a major economic activity among rural farmers. Its production contributes significantly to the GDP and further, livelihood security enhancement among rural folks. However, recent development has unveiled a situation of persistent low farm-level productivity among cocoa farmers which threatens their livelihood security. In view of this, we estimated the economic, technical, and allocative efficiencies among cocoa farmers and their determinants to help proffer relevant policy strategies to arrest the situation of low farm-level productivity. Using a multistage sampling procedure, we collected data from 750 cocoa farmers across the cocoa-growing regions of Ghana. To estimate the farm-level efficiency scores, we employed the stochastic frontier analysis and our results show that cocoa farmers generally exhibited significant levels of technical, allocative, and economic inefficiencies. We estimated the average technical, allocative, and economic efficiencies scores among the cocoa farmers to be 67%, 69%, and 51% respectively. The analysis of the determinants of technical, allocative, and economic inefficiencies revealed that farmer and farm-specific variables such as sex, household size, educational level, years of farming experience, frequency of extension contact, quality of extension received, use of climate smart adaptation technologies, farm size, farm labour and access to credit facilities significantly explain cocoa farm level efficiencies. Accordingly, we recommend that extension service providers and COCOBOD develop strategies to improve upon the quality of extension service delivery as well as incorporate the promotion and adoption of climate smart adaptation technologies into its productivity enhancement programmes for farmers.

Keywords: *Stochastic Frontier Analysis, Economic efficiency, efficiency drivers, cocoa production, Ghana*

Introduction

Cocoa is a major economic crop in Ghana, impacting greatly the socioeconomic well-being of the country. Evidence shows that cocoa contributes significantly to Ghana's economic performance in terms of GDP growth rate and macroeconomic balance (COCOBOD, 2019). The production and trading of cocoa beans represent a major economic activity for many people, especially those in the rural economy, contributing significantly to their livelihood security enhancement (e.g., income and food security). Given the socioeconomic importance of cocoa, the sector has seen much investment from the government all geared towards improving the sector's performance in terms of sustainable productivity growth. Despite the significant government investment in the sector, one key challenge that continues to bedevil the sector is the continuous decline in productivity due to the persistent low farm-level productivity (COCOBOD, 2019; Aneani et al., 2011; Onumah et al., 2013). Empirical evidence shows that the average farm-level productivity in Ghana is about 400-450kg/ha compared to the potential optimum of 1.5tons/ha (COCOBOD & Forest Initiative 2017; COCOBOD, 2019). Accordingly, it can be extrapolated that the average cocoa farmer loses about 76.7 per cent of his/her annual potential yield, thereby impacting negatively his/her potential welfare gains (e.g., income and food security).

In addressing the persistent low farm-level productivity that continues to characterised cocoa production in Ghana, policies usually resort to technological interventions, trying to make available to farmers some new technologies. This though being a step in the right direction often does not result in the anticipated outcomes. And this is largely due to the direction of the policy tilting towards increasing access to more technologies without recourse to the root course of low productivity, which is often attributed to the efficiency of production. Production economists have argued that output growth is not necessarily a function of the quantum of technologies introduced to farmers but the efficiency with which these technologies are utilised at the farm level (Onumah et al., 2013; Inkoom & Micah, 2017; Miao et al., 2017; Inkoom et al., 2020). We argued that to break the cycle of persistent low farm-level productivity in cocoa production, promoting farm-level efficiency is non-negotiable as it is the most cost-effective way to boost farm-level productivity more sustainably. This is because estimating the farm-level efficiencies of farmers helps to understand their economic and technical performance and the factors that limit or enhance their ability to do well technically and allocatively with respect to technology application and resource use (COCOBOD & Forest Initiative, 2017; COCOBOD, 2019; Aneani et al., 2011; Onumah et al., 2013; Kyei et al., 2011). We argued that given the limited ability of most developing countries concerning technological advancement, the most pragmatic way to engineer positive and sustainable productivity growth among farmers, given resource scarcity is to develop mechanisms that rather enhance the efficiency of production at the existing technology.

As posited by Onumah, Brummer, and Horstgen-Schwark (2010), efforts to improve efficiency as means of increasing productivity are more cost-effective than introducing new technologies if farmers are not optimising the use of the existing ones. Also, Inkoom and Micah, (2017) posited that through efficiency enhancement, farm firms can increase their productivity even in the absence of technical change. They further opined that efficiency estimation help to isolate the efficiency component of production activity to adequately measure its contribution to productivity growth. Across the literature it has been noted that farm-level efficiency measurement helps to identify the sources of efficiency and productivity differential among farmers, guiding the proffering of appropriate response policy initiatives (Danso-Abbeam et al., 2020; Danso-Abbeam, & Baiyegunhi, 2020; Miao et al., 2017; Kyei et al., 2011). With this, it can be posited that an understanding of farm-level efficiency and its determinants among cocoa farmers is a requirement to comprehensively address the problem of the persistent low farm-level productivity in cocoa production.

This calls for more independent empirical studies into full-scale farm-level efficiency in cocoa production (covering technical, allocative, and economic efficiencies) to help identify the best and most cost-effective way to boost productivity. Empirical evidence shows that previous efficiency studies in cocoa production have largely concentrated on technical efficiency estimation and as well as limited in its coverage in terms of the spatial dimension of the study areas (Aneani et al., 2011; Onumah et al., 2013; Kyei et al., 2011; Danso-Abbeam et al., 2020; Danso-Abbeam, & Baiyegunhi, 2020). The observed limited focus of previous efficiency studies in cocoa production has created a significant knowledge gap on the full-scale efficiency analysis (i.e., economic efficiency) which is capable of providing a much more comprehensive empirical knowledge on the overall farm level efficiencies among cocoa farmers and the drivers of same. Given resource constraints faced by cocoa farmers, we argue that improving economic efficiency will provide a credible pathway for improving farm-level productivity with the existing technology and help inform appropriate policy directions. This is because economic efficiency gives a holistic view of farm unit economic performance as it defines the ability of a farm unit operating at a given technology set to maximise output from minimal input combination at the minimum cost (i.e., cost minimising approach).

Economic efficiency simultaneously helps to unravel the technical efficiency level (indicative of technological performance) and the allocative efficiency level (indicative of resource-use performance) among farmers (Inkoom & Micah, 2017; Abdulai et al., 2017; Orisasona et al., 2019; Wollie et al., 2018). Thus, economic efficiency in the technical sense is the product of technical efficiency and allocative efficiency. Technical efficiency as a component of economic efficiency measures the ability of a farm unit using a given technology set to produce maximum output using a minimal input combination. Allocative efficiency as a component of economic efficiency defines the ability of a farm unit to maximise output at the least cost using a cost-minimising approach. Farrell (1957) who is credited as the pioneer of economic efficiency concepts, posited that for a better appreciation of the overall farm-level efficiency and its drivers, the estimation of economic efficiency presents a much better option. In addition, estimating the economic efficiency simultaneously helps to unravel the technological performance (indicates the technical efficiency level) as well as the resource-use performance (indicates the allocative efficiency level) of cocoa farmers. From the aforementioned, the empirical analysis of economic efficiency is important to determine the benefit that can be obtained by improving the performance in cocoa production with a given input set and the existing technology. Given the above, we, therefore, estimated the economic efficiency and its drivers in cocoa production to lend empirical support on how to improve the productivity enhancement programme currently being run by Ghana Cocoa Board (COCOBOD).

Methodology

Study Setting, Sampling Procedure, and Data Collection

The study was conducted across the major cocoa-growing regions in Ghana covering the Western region (comprising western north and south), Ashanti Region, Brong-Ahafo Region, Eastern Region, Central Region, and the Volta region. These regions are characterised by similar climatic conditions and an agro-based economy where a significant number of the population are into cocoa production. According to Ghana Cocoa Board data, about 800,000 farm families are estimated to be engaged in cocoa farming across these regions (COCOBOB, 2019). Following a cross-sectional survey design, we estimated the economic efficiency of cocoa farmers and the key internal and external variables that explain the observed efficiency differential among farmers. In arriving at the appropriate sample size that is representative of the population, we adopted Yamane's sample size determination formula and which is given as

$$n = \{N/[1 + N(e^2)]\}$$

where n represents the sample size to be estimated, N denoted the estimated population size of 800 000 cocoa farmers and "e" is the assumed margin of error (which for this study purpose was assumed to be 0.05). accordingly, substituting the defined parameter values into Yamane's formula gave an estimated sample size of 400 cocoa farmers. To cater for the effect of incomplete data and non-response rate as well as increased the degree of representativeness and minimise the margin of error, we increased the sample size to 720 by assuming a power effect of 80 per cent. This again was guided by the data requirement principle underlying the power of improving upon the accuracy and efficiency of the estimated econometric models in the study.

To select the 720 individual cocoa farmers to be part of the study, we followed a multistage simple random sampling approach and the process is outlined as follows. Firstly, three cocoa-growing regions (i.e., Western Region, Brong-Ahafo Region, and Central Region) were randomly selected from the list of major cocoa-growing regions listed above. The second stage involved the simple random selection of two major cocoa-growing districts from each of the three cocoa-growing selected from the first stage. In doing so, we first generated a list of major cocoa-growing districts for each of the three selected cocoa-growing regions, based on which two major districts from each of the sampled regions were then selected through a simple random lottery approach. The selected districts included Agona East and Assin Fosu from the Central Region, Asunafo North and Asunafo South from Brong-Ahafo Region, and Amefi West and Ellembelle from the Western Region. The next sampling stage involved the selection of major cocoa-growing communities in the six sampled cocoa-growing districts. In doing so, we first generate a list of major cocoa-growing communities for each of the six sampled districts. From the list generated, a simple random lottery approach was then used to simple randomly select six communities from each of the sampled districts, resulting in a sample frame of thirty-six cocoa-growing communities. The final sampling stage involved the selection of the individual cocoa farmers at the community level to constitute the 720 estimated sample size. At the community level, a list of all active cocoa farmers with not less than 2 hectares of farm size was generated for each of the thirty-six cocoa communities. This benchmarking as an inclusion and exclusion criteria were aimed at getting farmers within the category of medium to large-scale farm size. From the list, twenty farmers were then randomly selected from each community, resulting in a total sample size of seven hundred and twenty (720) cocoa farmers from whom data was collected for the study. In our survey, we developed a structured interview schedule as our data collection instrument to collect data from the seven hundred and twenty sampled cocoa farmers from across the cocoa-growing regions in Ghana. The structured interview schedule instrument was used to collect data on the farmer and farm-specific variables, production, and cost data.

Data processing and analysis

The data collected from the survey were processed using Microsoft Excel software and R Programming Environment software. To analyse the farmer and farm-specific variables, we employed descriptive statistical tools such as means, standard deviations, frequencies, and percentages. Again, we employed the Efficiency Effect Stochastic Frontier model and Tobit regression model as the econometric tools to analyse the farm-level economic efficiency and its determinants. The formal specification of the Efficiency Effect Stochastic Frontier model and Tobit model as applied in our study are discussed in the subsequent sections.

Efficiency Effect Stochastic Frontier Model for Estimating Economic, Technical and Allocative Efficiencies

To analyse cocoa farmers' farm-level economic, technical and allocative efficiencies, we employed the stochastic frontier model as originally and independently proposed by Aigner, Lovell, and Schmidt (1977), and Meeusen and Van den Broeck (1977). This was implemented under the efficiency effect frontier model as proposed by Battese and Coelli, (1995). The efficiency effect frontier model follows a one-stage modelling approach in which variables that influence the inefficiency term are implicitly and explicitly included in the stochastic frontier model specification directly (Schmidt, 2011; Wang, 2002; Wang & Schmidt, 2002; Battese & Coelli, 1995). In the empirical literature, the functional specification of the stochastic frontier models (i.e., production frontier and cost frontier) has largely followed the Cobb-Douglas or Translog functional forms respectively. The two functional forms have their strengths and weakness which demands consideration when estimating stochastic frontier models (see, Kumbhakar et al., 2020; Henningsen, 2020; Wheat et al., 2019, Donnell, 2018; Heathfield, 2016; Coelli et al., 2005; Kumbhakar & Lovell, 2003; Kumbhakar, 1997). Accordingly, for theoretical and empirical soundness, it is required that to avoid potential violation of central theoretical underpinnings, the choice of which model to use should rest on the suitability of the model to the dataset and consistency with the assumed theoretical underpinnings of the research objective (Kumbhakar et al., 2020; Wheat et al., 2019; O'Donnell, 2018; Sauer et al., 2006; Coelli et al., 2005; Kumbhakar & Lovell, 2003; Greene, 2007). In line with this, we estimated both Cobb-Douglas and Translog functional forms for both the stochastic production frontier and cost frontier models. The two estimated models were then tested for model fitness to find out which one best fits the dataset and appropriately represents the production technology and optimising behaviour of the ith production unit. From the estimated stochastic production frontier and cost frontier functions, we determine the output and cost elasticities with respect to the inputs and input prices as employed by the ith production unit. Based on the duality concepts, the three efficiency components (economic, technical and allocative) as proposed by Farrell (1957) were estimated from stochastic production and cost frontier models. The formal specification of the efficiency effect stochastic production frontier and cost frontier models as in this study are explained below.

Formal specification of the stochastic production frontier model

The standard efficiency effect stochastic production frontier model for estimating the technical efficiency in cocoa production was specified as:

$$y_i = f(x_i, \beta) + v_i - u_i(z_i, \theta), \qquad u_i(z_i, \theta) \geq 0 \qquad \text{Eqn. 1}$$

Where y_i represents output level for the i^{th} cocoa farmer employing a vector of inputs x_i given a technology set, z_i, denotes exogenous variables that explain the efficiency level, β, and θ denote unknown parameters to be estimated, v_i *and* $-u_i$ represents the composed error terms of noise and the non-negative technical inefficiency effect respectively. Theoretically, equation 1 assumes that the boundary of the production function represents the best productivity performance, and such the function differentiates the frontier output $[y_i^*]$ from the observed output $[y_i]$ (Inkoom et al., 2020; Coelli et al., 2005). Premised on this we estimated the technical efficiency score of the i^{th} cocoa farmer following equation 2 as specified below:

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(\beta x_i) + v_i - u_i}{f(\beta x_i) + v_i} = e^{-u} \qquad \text{Eqn. 2}$$

Generally, the estimated technical efficiency score as defined in Eqn. 2 is bounded between a value of 0 and 1. If the estimated TE score is found to be 0 (i.e., u = 1), it means that the production unit (i.e., cocoa farmer) is considered to be technically inefficient, which suggests that the farmer is operating below the optimal frontier. If the estimated TE value is 1 (i.e., u = 0), then it can be said that the production unit is technically efficient in production, thus operating on the optimal frontier.

Formal specification of the stochastic cost frontier model

Following the self-duality principle of the production and cost functions, we estimated the stochastic cost frontier model, assuming a cost minimisation framework to derive the economic efficiency scores of the ith cocoa farmer. The formal specification of the stochastic cost frontier dual of the stochastic production frontier model was specified as:

$$C_i = f(w_i, y_i, \beta) + v_i + u_i(z_i, \theta), \qquad u_i(z_i, \theta) \geq 0 \qquad \text{Eqn. 3}$$

Where C_i represents the minimum cost to product output y_i, w_i represents the price of vector inputs, z_i, denotes exogenous variables that explain the efficiency level, and β and θ denote a vector of unknown parameters to be estimated. The v_i is the error component that accounts for stochastic noise effects and u_i is the error component that accounts for the cost inefficiency effect. Theoretically, equation 3 assumes that the boundary of the cost function represents the best economic performance relative to the cost minimisation objective, and such the function differentiates the minimum cost $[\eta_i]$ from the observed cost $[\eta_i^*]$ (Inkoom et al., 2020; Coelli et al., 2005). Premised on this we estimated the economic efficiency score of the i^{th} cocoa farmer following equation 4 as specified below:

$$EE_i = \frac{\eta_i}{\eta_i^*} = \frac{f(w_i, y_i, \beta) + v_i + u_i}{f(w_i, y_i, \beta) + v_i} = e^{-u}. \qquad \text{Eqn. 4}$$

Following Farrell (1957), the economic efficiency score as estimated from the stochastic cost frontier model is bounded between 0 and 1. An efficiency score of 1 (i.e., u =0) suggests that the production unit (cocoa farmer) is economically efficient and an efficiency score of 0 (i.e., u = 1) means the production unit (cocoa farmer) is economically inefficient in production.

As posited by Farrell (1957), the overall cost (economic) efficiency is a product of technical efficiency and allocative efficiency. Accordingly, haven estimated the economic efficiency from the cost frontier, we decomposed it into its respective efficiency components (i.e., technical efficiency and allocative efficiency) following the duality approach. In principle, the cost frontier as specified in equation 3 is said to be a self-dual function of the production frontier as specified in equation 1. As such the technical efficiency estimate derived from the decomposition of economic efficiency as specified in equation 3 does not significantly deviate from that gotten from equation 2. Following the decomposition procedure, the allocative efficiency of the ith farmer can be expressed as the ratio of economic efficiency to technical efficiency and this is mathematically stated in equation 5:

$$AE_i = \frac{EE_i}{TE_i} \qquad \text{Eqn. 5}$$

The estimated value of AE as specified in equation 5 lies between 0 and 1. An AE value of 0 means the production unit is allocatively inefficient and a value of 1 means the production unit is allocatively efficient in production.

Parameterisation of efficiency estimator

With the SFA model, it is assumed that $v_i \sim iidN(0, \sigma^2)$ and $u_i \sim iidN^+(0, \sigma^2)$, and that these two error terms are distributed independently of each other and the regressors (Coelli et al., 2005; Battese & Coelli, 1995; Kumbhakar, & Lovell, 2003). Fundamentally, the appropriate efficiency estimator of cocoa farmers is conditioned on the conditional expectation of the inefficiency effect term (u). Accordingly, Battese and Corra (1977) posited that the firm-specific technical or cost efficiencies can be estimated following a reparameterization of the inefficiency effect term (u) based on the gamma distribution, and this is specified as:

$$\gamma = \frac{\sigma^2 u}{\sigma^2} = \frac{\sigma^2 u}{(\sigma^2 v + \sigma^2 u)} \qquad \text{Eqn. 6}$$

Theoretically, the value of gamma estimated from equation 6 helps to explain the contributing effects of both the inefficiency effect error term and the stochastic noise effect error term to the deviations from the frontier. The gamma parameter (γ) as specified in equation 6 is bounded between 0 and 1. A value of $\gamma = 1$ means that the deviations from the efficiency frontier are entirely due to technical or cost (economic) inefficiency effects. On the contrary, if gamma is estimated to be 0, then the deviations from the efficiency frontier are entirely attributable to the stochastic noise effect. Accordingly, with $0 < \gamma < 1$ the variability in the estimated efficiencies is said to be characterized by the presence of both the inefficiency effect and stochastic noise effect.

Empirical specification of the stochastic production and cost frontier models as applied in this study was specified as follows:

We estimated the Cobb-Douglas and Translog functional forms of the stochastic production and cost frontier models following the maximum likelihood estimation approach. The two models under the production and cost frontiers were then subjected to model fitness test to check which of them best fit the data set and appropriately represents the production technology and optimising behaviour of the ith cocoa farmer. The empirical model specifications for the Cobb-Douglas production (Equation 7) and cost (Equation 8) frontier models as applied in this study were specified as follows:

$$\log(y_i) = \beta_0 + \beta_1 logx_1 + \beta_2 logx_2 + \beta_3 logx_3 + \beta_4 logx_4 + v_i - u_i \quad \text{Eqn. 7}$$

$$\log(C_i) = \beta_0 + \beta_1 logw_1 + \beta_2 logw_2 + \beta_3 logw_3 + \beta_4 logw_4 + \beta_5 log\ y + v_i + u_i \quad \text{Eqn. 8}$$

The empirical Translog production (Equation 9) and cost (Equation 10) functions were specified as follows:

$$\begin{aligned} &log(y_i) = \beta_0 + log(x_1) + log(x_2) + log(x_3) + log(x_4) \\ &+I(0.5 * log(x_1)^2) + I(0.5 * log(x_2)^2) + I(0.5 * log(x_3)^2) \\ &+I(0.5 * log(x_4)^2) + I(log(x_1) * log(x_2)) + I(log(x_1) * log(x_3)) \\ &+I(log(x_1) * log(x_4)) + I(log(x_2) * log(x_3)) + I(log(x_2) * log(x_4)) \\ &+I(log(x_3) * log(x_4)) + v_i - u_i \qquad \text{Eqn. 9} \end{aligned}$$

$$\begin{aligned} &log(C_i) = log(w_1) + log(w_2) + log(w_3) + log(w_4) + log(y) \\ &+I(0.5 * log(w_1)^2) + I(0.5 * log(w_2)^2) + I(0.5 * log(w_3)^2) \\ &+I(0.5 * log(w_4)^2) + I(log(w_1) * log(w_2)) + I(log(w_1) * log(w_3)) \\ &+I(log(w_1) * log(w_4)) + I(log(w_2) * log(w_3)) + I(log(w_2) * log(w_4)) \\ &+I(log(w_3) * log(w_4)) + I(0.5 * log(y)^2) + I(log(y) * log(w_1)) \\ &+I(log(y) * log(w_2)) + I(log(y) * log(w_3)) + I(log(y) * log(w_4)) + v_i + u_i \qquad \text{Eqn. 10} \end{aligned}$$

Where u_i the inefficiency effect term in both Equations 7, 8, 9, and 10 are expressed as a function of certain explanatory variables:

$$u_i = \theta_0 + \theta_1 z_1 + \theta_2 z_2 +, \ldots, +\theta_{12} z_{11} + e_i \qquad \text{Eqn. 11}$$

The definition of variables included in empirical models as specified in equations 7, 8, 9, and 10 are presented in Table 1.

Second, the drivers of allocative efficiency were estimated under the Tobit regression model. This becomes necessary as allocative efficiency is a derived estimate from economic and technical efficiency, thus making it difficult to predict its drivers in the one-stage estimation approach.

Theoretically, the Tobit regression model is an econometrics model as proposed by Tobin (Tobin, 1958) is a truncated or censored regression modelling that helps to describe the relationship between a non-negative dependent variable y_i and independent variable x_i . The foundational principle of the Tobit model which informed our choice of it is that it can handle equations with restricted threshold like efficiency estimates which ranges from 0 to 1 (Tobin, 1958; Gwahula, 2013; Dharmendra & Bashir, 2015; Djalilov & Piesse, 2014; Khalad & Mazila, 2014). The standard Tobit regression model as followed in this study is specified as

$$y_i^* = \beta x_i^{'} + e_i \quad ; \varepsilon_o \approx N(0, \sigma^2) \qquad \text{Eqn. 14}$$

$$y_i = \{ {}^{0}_{y_i^*} \text{ if } {}^{y_i^* \leq 0}_{y_i^* > 0} \qquad \text{Eqn. 15}$$

Where, the subscript $i = 1, \ldots, N$ indicates the observation, y_i and y_i^* are vectors of observed and unobserved ("latent") variables respectively, x_i is a vector of explanatory variables, β is a vector of unknown parameters, and is e_i the random or stochastic error term. The empirical Tobit regression model as estimated in the study was specified as follows:

$$u_{AE} = \theta_0 + \theta_1 z_1 + \theta_2 z_2 +, \ldots, +\theta_{12} z_{11} + e_i \qquad \text{Eqn. 16}$$

The definition of variables included in the empirical model as specified in Equation 16 is presented in Table 1.

Table 1: Definition of variables included in the empirical models (i.e., Equations, 7,8,9,10,11,13,14 and 16) and their summary statistics

Variables	Definition	Measurement	Descriptive statistics	
y_i	Output quantity of cocoa	kg/ha	Mean = 1000kg/ha	Std. Dev. = 90kg/ha
C_i	Minimum total cost of production	GH¢/ha	Mean = 4032.38 GH¢/ha	Std. Dev. = 1273.18 GH¢/ha
u_{EE}	Economic inefficiency effect	Continuum of 0 to 1	Mean = 0.4097	Std. Dev. = 0.1604
u_{TE}	Technical inefficiency effect	Continuum of 0 to 1	Mean = 0.3732	Std. Dev. = 0.2618
u_{AE}	Allocative inefficiency effect	Continuum of 0 to 1	Mean = 0.6185	Std. Dev. = 0.1496
x_1	Quantity of labour used	man-day/ha	Mean = 82 man-day/ha	Std. Dev. = 37 man-day/ha
x_2	Quantity of fertilizer used	kg/ha	Mean = 199 kg/ha	Std. Dev. = 41 kg/ha
x_3	Quantity of agrochemicals used	Litres/ha	Mean = 2 litres/ha	Std. Dev. = 1 litres/ha
w_1	Unit cost of labour	GH¢/ha	Mean = 37.58 GH¢/ha	Std. Dev. = GH¢/ha
w_2	Unit cost of Fertilizer	GH¢/ha	Mean = 87.73 GH¢/ha	Std. Dev. = GH¢/ha
w_3	Unit cost of Agrochemicals	GH¢/ha	Mean = 39.22 GH¢/ha	Std. Dev. = GH¢/ha
x_4 *and* w_4	Cost of capital	GH¢/ha	Mean = 507 GH¢/ha	Std. Dev. = 159 GH¢/ha
z_1	Land size	Hectares (ha)	Mean = 5.1ha	Std. Dev. = 1.8ha
z_2	Sex of respondent	Dummied: "1 = Male" ; "0 = Female"	Male = 67.22 %	Female =32. 78 %
z_3	Age of respondent	Number of years	Mean = 47 years	Std. Dev. = 11years
z_4	Years of Education	Average years in school	Mean = 8.60 years	Std. Dev. = 5years
z_5	Household size of respondents	Count of people	Mean = 5	Std. Dev. = 2
z_6	Farming experience	Number of years	Mean = 18.42 years	Std. Dev. = 9.42 years
z_7	Extension contact	Frequency of contact	Mean = 7	Std. Dev. = 2
z_8	Access to credit facilities	Dummied: "1 = Yes"; "0 = Otherwise"	Yes =53.89 %	Otherwise = 46.11%
z_9	Farm-based organization membership	Dummied: "1 = Yes"; "0 = Otherwise"	Yes = 52.8 %	Otherwise = 47.92 %
z_{10}	Off-farm economic engagement	Dummied: "1 = Yes"; "0 = Otherwise"	Yes = 50.97 %	Otherwise = 49.03%
z_{11}	Quality of extension service received	Scale of 1 to 10	Mean = 6.99	Std. Dev. = 2.18
z_{12}	Use of climate smart adaptation	count of CSA used	Mean = 6	Std. Dev. = 2
βs and θs	Unknown parameters to be estimated			
v_i	Stochastic noise effect term			
u_i	Inefficiency effect term			
e_i	Error term; $\{e_o \approx N(0,\sigma^2)\}$			

Results and Discussion

Estimates of the Efficiency Effect of Stochastic Production and Cost Frontier Models

To satisfy theoretical consistency and data suitability requirement, we estimated both the Cobb-Douglas and Translog functional specifications for the efficiency effect stochastic production and cost frontier models and then tested them for model fitness. From the diagnostic analysis, as indicated by the Log-Likelihood ratio test results (see, model summary in Table 2), the Cobb-Douglas functional form was found to give the best model fitness to the data set and appropriately represents the production technologies and the optimising behaviour at the individual farm level than the Translog functional specification. Given that the log-likelihood ratio test favoured the Cobb-Douglas functional specification as appropriately and accurately fitting the data and thus producing an efficient estimate for the stochastic production and cost frontier models, we selected to present the Cobb-Douglas Model estimates for the efficiency effect stochastic production and cost frontier models as contained in Tables 2a and 2b.

Table 2a: Maximum Likelihood Estimates of Cobb-Douglas Stochastic Production Frontier Model

Model Estimates for the Efficiency Effect of Stochastic Production Frontier Model				
Variable	**Coefficient**	**Std. Error**		**Z value**
Constant	-4.8259***	0.1222		-39.5080
Log (labour)	0.6345***	0.0294		21.5897
Log (Fertilizer)	0.6447***	0.1551		4.1568
Log (Agrochemical)	-0.0353***	0.0090		-3.9242
Log (Capital)	0.4617***	0.0107		43.1095
Model summary				
Sigma	0.0279***	0.0019		14.7247
Gamma	0.6679***	0.1536		4.3471
Loglikelihood ratio test of model fitness				
	LogLik.	DF	χ^2	p-value
Cobb-Douglas Production Frontier	401.46			
Translog Production Frontier	319.72	10	2.5597	0.99

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

Table 2b: Maximum Likelihood Estimates of Cobb-Douglas Stochastic Cost Frontier Model

Model Estimates for the Efficiency Effect Stochastic Cost Frontier Model				
Variable	**Coefficient**		**Std. Error**	**Z value**
Constant	4.5285***		0.1456	31.0939
Log (Labour cost)	0.3002***		0.6374	12.9683
Log (Fertilizer cost)	0.2489***		0.0311	7.9820
Log (Agrochemical cost)	-0.6708***		0.0761	-8.8058
Log (Capital)	0.3342***		0.0231	14.4390
Log (Output)	0.2474***		0.0255	9.6873
Model summary				
Sigma	0.0242***		0.0017	14.1624
Gamma	0.9499***		0.0690	13.7616
Loglikelihood ratio test of model fitness (SCFM)				
	Loglik.	DF	χ^2	p-value
Cobb-Douglas Cost Frontier	578.93			
Translog Cost Frontier	325.59	15	18.2568	0.2521
Significance codes: '' 0.01 '**' 0.05 '*' 0.1***				

The model fitness test further suggests that the efficiency effect stochastic frontier models present efficient and consistent results. Furthermore, the estimated sigma and gamma coefficients for both the production and cost frontier models were found to be statistical and significantly different from zero, suggesting a good fit of the models and the correctness of the specified distributional assumptions. Additionally, the estimated gamma coefficients of 0.6679 for the production frontier and 0.9499 for the cost frontier indicate that the presence of the inefficiency effect does affect the production technology and optimising behaviour of the individual cocoa farmer. Hence, we can conclude that technical, economic, and allocative inefficiencies are significant in explaining the variability in farm-level productivity among cocoa farmers in Ghana. Theoretically, gamma picks a value between zero and one, indicating the importance of the inefficiency term. A value of zero means that the inefficiency term "u" is irrelevant or absent. On the other hand, if gamma is equal to one, then the noise or stochastic term "v" is completely irrelevant and that inefficiency (i.e., Technical, economic, and inferably allocative inefficiencies) accounts for all the observed deviation from the production or cost frontier (Henningsen, 2020; Inkoom & Micah, 2017). Drawing from this, the estimated gamma coefficient of 0.6679 and 0.9499 for both production and cost frontier models implies that both inefficiency and stochastic noise effects are important in explaining any observed deviations from the production and cost frontiers. Nonetheless, inefficiency effects are considered the most important factor. This is because a composite analysis of the gamma values following Henningsen (2020) in the R Programming Environment Language revealed that, about 90 per cent of the observed total inefficiency variance is attributable to technical, allocative and economic inefficiencies effect, with stochastic noise effect accounting for about 10 per cent of the total inefficiency variance. The model estimates as presented in Table 2a reflect the contributions of the production inputs to changes in output elasticity and their cost implications on the performance of cocoa farmers in Ghana. The result from the stochastic production frontier model as presented in Table 2a shows that the estimated output elasticities were monotonically increasing for labour, fertilizer, and capital inputs utilisation per hectare of land, but monotonically nonincreasing for agrichemical input utilisation per hectare of land. Furthermore, it was observed that all the input variables were significant in defining the production technology at the farm level. This implies that for meaningful productivity growth in cocoa production, optimal and efficient use of labour, fertiliser, capital, and agrochemicals are critical. In technical terms, the results suggest that a percentage increase in fertiliser, labour and capital inputs would lead to a 0.6345 per cent, 0.6447 per cent, and 0.4717 per cent increase respectively in output. The observed input-output relationship suggests that there is some level of optimal allocation of labour and fertiliser inputs by farmers. Accordingly, an optimal upward adjustment in their utilisation would strengthen the potential of attaining maximum farm-level productivity in cocoa production. The negative and significant coefficient of agrochemical inputs suggests that a percentage increase in the agrochemical input usage leads to a 0.0353 per cent decrease in output, thereby impacting negatively farm-level productivity. This suggests a potential misallocation or excessive use of agrochemicals by farmers. Thus, a radial reduction in agrochemical usage to an optimal level will lead to a positive output elasticity of production. Furthermore, the elasticity of scale was estimated to be 1.7762, which means that the production technology exhibits an increasing return to scale and this suggests that total factor productivity increases at an increasing rate when there is an optimal proportional increase in all input quantities. Accordingly, a relative increase in the output quantity of cocoa is almost more than double the relative increase of the aggregate input quantity. This consequently implies that ensuring efficient and optimal use of labour, fertiliser, capital, and agrochemical per hectare of land at the given technology can significantly increase productivity in cocoa production.

For the cost frontier model, Table 2b reveals that the estimated cost elasticity coefficients were all monotonically nondecreasing for Labour, fertiliser, and Capital input prices except for agrochemical input prices. Additionally, the coefficient of the output quantity was found to be non-negative, suggesting that the cost function is monotonically nondecreasing in output quantities. The estimated coefficients of the explanatory variables in the stochastic cost frontier model were all found to be significant. The estimated positive cost elasticities of labour, capital, and fertiliser imply the total cost of production increases by 0.3002 per cent, 0.2489 per cent, and 0.3342 per cent as the cost share of these variable inputs increases by one per cent. Furthermore, the estimated negative coefficient of agrochemical input, suggests the total cost of production decreases by 0.6708 per cent as the cost share of agrochemicals increases by one per cent. One probable reason that could account for the observed cost-share behaviour of agrochemical input price is the potential impact of the cocoa mass spraying programme which absorbs a greater percentage of the cost incurred in the control of disease and pests on the average cocoa farm across the country. Again, the estimated positive coefficient of output quantity reflecting the cost flexibility, suggests that a per cent increase in output quantity contributes to the marginal increase in the cost build-up by 0.2474 per cent. Following the cost flexibility concept, an inverse of 0.2471 gives an elasticity of size value of 4.0420. This means that achieving a cost minimisation of one per cent increases the output quantity of cocoa by 4.0420 per cent.

Distribution of Farm-level Technical, Allocative, and Economic Efficiencies among Cocoa Farmers

Figure 1 presents summary statistics on the farm-level efficiency estimates covering economic, technical, and allocative efficiencies respectively. The summary statistics estimated include the mean efficiency estimates with their standard deviations as well as the maximum and minimum estimates across the three efficiency components.

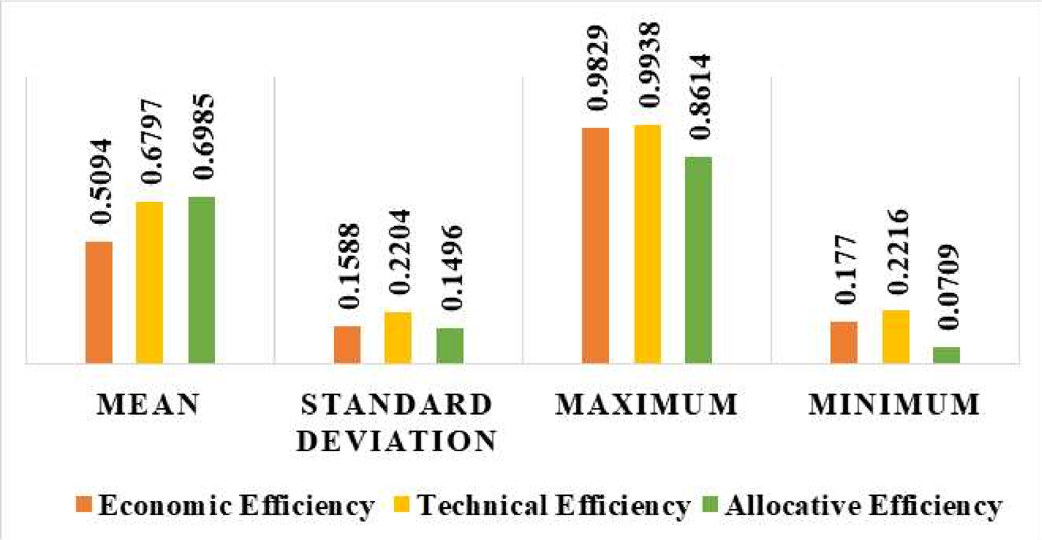

Figure 1: Summary Statistics of Farm-level Economic Efficiency, Technical Efficiency, and Allocative Efficiency Estimates

The general outlook from the three efficiency estimates shows that farmers were not fully efficient technically, allocatively, and economically, with a considerable level of variation existing in the economic, technical, and allocative efficiencies among cocoa farmers, and this affirms the general observation in previous empirical studies (for example, Aneani et al., 2011 Danso-Abbeam et al., 2012; Onumah et al., 2013; Besseah & Kim, 2014) The estimated technical efficiency estimates range between 0.2216 to 0.9938, with a mean of 0.6797 and a standard deviation of 0.2204. The mean technical efficiency of 0.6797 indicates that farmers produce about 67.97 per cent of potential output given the level of farm production technology available. The mean estimate also indicates a 67.97% technological efficiency, implying that farmers exhibit a moderate ability to achieve the minimum input combination to produce maximum output. The mean estimate of technical efficiency further suggests that farmers were about 0.32 (i.e., 32 per cent) below the efficient and optimal frontier that maximises output and utility (i.e., profit). This means that there is about 33 per cent technical inefficiency in cocoa production. The technical efficiency performance as observed from our study when compared to other study findings in cocoa production shows some differentials. For instance, the mean technical efficiency of 0.6797 was found to be higher than the mean technical efficiency estimates of 0.4782 and 0.49 as observed by Besseah and Kim, (2014) and Danso-Abbeam et al. (2012) among cocoa farming households in Ghana. The study results as portrayed in Figure 1 again revealed that the allocative efficiency estimates among cocoa farmers range between 0.0709 to 0.8614, with a mean of 0.6985 and a standard deviation of

0.1496. The estimated mean allocative efficiency of 0.6985 indicates that farmers were about 69.85 per cent efficient in their allocative potential, thereby operating at 0. 0.3015 (i.e., 31 per cent) below the optimal frontier that maximises profit at the minimum cost. It can thus be inferred that farmers exhibited on average a 69 per cent resource-use efficiency among cocoa farmers, which suggests a moderate ability of farmers in producing maximum output using a cost-minimising input proportion. The estimated mean allocative efficiency by implication reveals that farmers are relatively efficient in producing a given level of cocoa output using the cost-minimising input ratio. Further, the mean allocative efficiency estimate means that the average farmer's cost-shaving potential in relation to the most efficient farmer stands at about 19.76 per cent [i.e., (1-(0.69/0.86) *100)]. In comparison to the empirical literature on cocoa production, the mean allocative efficiency of 0.69 from our study is found to be consistent with similar findings by Ogunya and Tijani, (2022), who also found that the average allocative efficiency among cocoa farmers in Nigeria was about 0.69. On the state of economic efficiency, as shown in Figure 1, the estimated economic efficiency of cocoa farmers ranges between 0.1770 to 0.9829, with a mean of 0.5094 and a standard deviation of 0.1588. The mean economic efficiency of 0.5094 indicates that farmers on average were operating about 0.49 below their optimum frontier output which maximises profit from the best cost minimising input combination. Additionally, the mean estimate indicates a 51 per cent technological and resource-use efficiency potential among cocoa farmers. This by inference suggests a moderate ability of farmers to produce maximum output from a minimal input combination at the least cost possible. In other words, farmers' ability to maximise output with minimal input combination at the least cost possible was reduced by a 49 per cent point deviation. In relation to similar empirical findings on the estimation of economic efficiency among cocoa farmers, the mean economic efficiency of 0.5094 as estimated from our study was found to be lower than the average economic efficiency score of about 0.60 among cocoa farmers in Nigeria as estimated by Ogunya and Tijani, (2022). Figure 2 presents the percentage distribution of farmers according to their farm-level efficiency estimates. Following the quartile distribution principle, the efficiency score was quarterised. The quarterisation led to four efficiency profile categories. The description of the categories is as follows: low-efficiency profile (0 – 0.24), moderately low-efficiency profile (0.25 – 0.49), moderately high-efficiency profile (0.51 – 0.74), and High-efficiency profile (0.75 – 1.00).

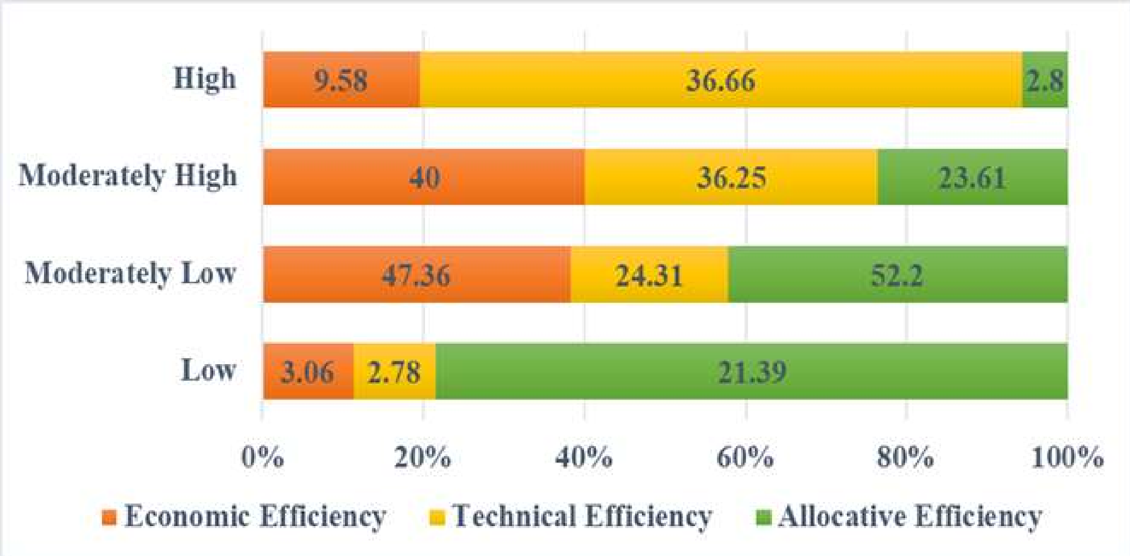

Figure 2: Percentage distribution of farmers according to their technical efficiency, allocative efficiency, and economic efficiency estimates

As illustrated in Figure 2, the percentage distribution shows that the majority (i.e., about 72.91 %) of the farmers exhibited a moderately high to a high level of technical efficiency profile, with few of them (2.78 %) showing a low level of technical efficiency profile at the farm level. From this it can be inferred that majority of the farmers when given the needed technical training can significantly be improved their farm-level performance given the existing technology. We further observed from the results that when it comes to allocative efficiency, the majority (i.e., about 75.81 %) of the farmers exhibited a moderately low to moderately high level of allocative efficiency profile. In addition, we observed that about similar situation happened for economic efficiency, where about 87.37 per cent of the farmers exhibited a moderately low to a moderately-high level of farm-level economic efficiency profile. This means, there is a need for urgent technical and farm-management economic training for cocoa farmers to help improve their technological and economic performance in production. The significant variations in efficiency distribution among farmers as observed in Figure 2 tend to collaborate with previous study findings on the distribution of technical, allocative, and economic efficiencies among farmers in cocoa production in Ghana (Aneani et al., 2011; Onumah et al., 2013; Danso-Abbeam & Baiyegunhi, 2020).

Drivers of Farm-level Technical, Allocative, and Economic Efficiencies of Cocoa Farmers

In empirical efficiency analysis, the estimated level of farm-level efficiencies is often not enough to guide appropriate policy intervention. Thus, it becomes necessary to identify the sources of efficiency differentials among farmers. This helps to identify factors contributing to the technical, allocative, and economic inefficiencies among farmers, which when addressed help position farmers to achieve sustainable and higher productivity growth. To ascertain the potential sources of the variation in the technical, allocative, and economic efficiencies among cocoa farmers, we estimated two separate models in line with theoretical soundness and consistency. First, in estimating the drivers of technical and economic efficiency, the one-stage efficiency effect stochastic production and cost frontier models were employed. After that, the Tobit regression model was used to analyse the drivers of allocative inefficiency. The two model results are accordingly presented in Table 3. In empirical efficiency analysis, the estimated level of farm-level efficiencies is often not enough to guide appropriate policy intervention. Thus, it becomes necessary to identify the sources of efficiency differentials among farmers. This helps to identify factors contributing to the technical, allocative, and economic inefficiencies among farmers, which when addressed help position farmers to achieve sustainable and higher productivity growth. To ascertain the potential sources of the variation in the technical, allocative, and economic efficiencies among cocoa farmers, we estimated two separate models in line with theoretical soundness and consistency. First, in estimating the drivers of technical and economic efficiency, the one-stage efficiency effect stochastic production and cost frontier models were employed. After that, the Tobit regression model was used to analyse the drivers of allocative inefficiency. The two model results are accordingly presented in Table 3.

Table 3: Drivers of farm-level economic, technical, and allocative inefficiencies among cocoa farmers

Variable	Economic Inefficiency Model		Technical Inefficiency Model		Allocative Inefficiency model	
	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	0.1566	0.1626	2.5698***	0.1131	0.9394***	0.0604
Sex	-0.0450	0.1327	-0.3354*	0.1811	-0.0312***	0.0072
Age	0.0149	0.0803	0.0473	0.1176	0.0121	0.0294
Household size	-0.0096	0.0334	-0. 2067**	0.0430	-0.0219	0.0161
Education	-0.1196***	0.0127	-0.2146***	0.0179	-0.0254***	0.0061
Farming experience	-0.1446***	0.0087	-0.0430**	0.0122	-0.0193**	0.0076
Farmer association membership	0.0024	0.0126	0.0142	0.0165	0.0039	0.0046
Frequency of extension contact	-0.4192***	0.0318	-0.3480***	0.0424	-0.0826***	0.0165
Extension service quality	-0.3364***	0.0297	-0.8547*	0.3818	-0.4890***	0.0165
Climate Smart Adaptation	-0.3009***	0.0480	-0.3864**	0.0466	-0.2805*	0.1596
Farm size	-0.1074***	0.0185	-0.7046***	0.3152	-0.0743***	0.0060
Farm labour	0.1831***	0.0226	0.7677***	0.0464	0.0125***	0.0049
Off-farm economic activity	0.0022	0.0134	0.0486	0.1828	0.2100	0.1368
Access to credit	-0.0272*	0.0150	-0.1103***	0.0182	-0.0764***	0.0074

Signif. codes: '***' 0.01 '**' 0.05 '*' 0.1

Note: Coef. = parameter coefficient; SE = standard error

The results as portrayed in Table 3 shows that the sex of the farmer was a significant driver of the observed technical and allocative inefficiencies at 0.1 and 0.01 significance level respectively. In particular, the estimated coefficient of sex was negative in both technical and allocative inefficiency models. This means that the average female cocoa farmer was more technically and allocatively inefficient than her male counterpart. In other words, compared to the average male farmer, the average female farmer was less technically and allocatively efficient in production. This could probably to attributed to the socio-cultural and economic factors that favour men but limit women when it comes to access to information and production resources. This observed influence of sex on farm-level efficiency differentials among cocoa farmers as witnessed in our study confirms similar study findings where male cocoa farmers were found to be more efficient in production as compared to female farmers (see, for example, Danso-Abbeam & Baiyegunhi, 2020; Besseah & Kim, 2014; Danso-Abbeam et al., 2012). Another important variable that significantly explained the variation in farm-level inefficiency was household size. Farm household size as a variable was found to be negative and significantly influenced technical inefficiency variation among farmers at a significant level of 0.05. This means that cocoa farmers with more household members were less technically inefficient in production. Accordingly, it can be inferred that farmers with a higher number of household members had the benefit of social capital which contributed to the number of available farm hands to carry out timely and effective production activity. The observed positive impact of larger households on farm-level technical efficiency collaborates with the findings of Danso-Abbeam et al. (2012) who also found that household size positively influenced technical efficiency among cocoa farmers in the Bibiani-Anhwiaso-Bekwai District of Ghana.

From the three model results, years of farming experience were found to have a negative and significant relationship with technical, allocative, and economic inefficiencies. This suggests that an increase in years of farming experience increases the likelihood of farmers attaining a higher level of efficiency. That is more experienced farmers were less inefficient as compared to their counterparts. This can be attributed to the potential experiential knowledge acquisition that comes with years of experience. The observed impact of farming experience on farm-level efficiency in our study affirms similar findings by other studies (see, for example, Ogunya & Tijani, 2022; Onumah et al., 2013). We further observed from our study that, education as a farmer-specific variable negatively and significantly influenced the technical, allocative, and economic inefficiencies among cocoa farmers. The results as indicated in Table 3 suggest that receiving some level of education increases the likelihood of cocoa farmers being technically, allocatively, and economically more efficient (i.e., less inefficient) in production. As such, it can be adduced that education enhances the cognitive ability of farmers to carry out their production active efficiently, hence given reducing the probability of higher levels of technical, allocative, and economic inefficiencies among cocoa farmers. Again, extension service as an important institutional variable significantly and negatively influenced economic, technical and allocative inefficiencies among farmers. Accordingly, efficient and effective utilisation of extension services would increase the propensity of farmers to achieve higher productivity growth. Another novel finding from our study was that not only is the frequency of extension contact important in predicting farm-level efficiency deferential but the quality of the extension service received by the farmers. for instance, our results as portrayed in Table 3 shows that access to quality extension service increases the propensity of cocoa farmers to be technically, allocatively, and economically more efficient (i.e., less inefficient) production. It is therefore important for cocoa extension service providers to ensure that they provide frequent and quality extension service to farmers to increase the likelihood of achieving higher productivity growth. In comparison to other efficiency studies in cocoa production, our study findings on the significant and positive impact of education and extension contact on farm-level efficiency confirm findings by Ogunya and Tijani, (2022) who likewise observed a positive impact of education and extension contact on the economic, technical and allocative efficiency level among cocoa farmers in Nigeria. Furthermore, we observed that the observed impact of education on the technical efficiency of cocoa farmers deviates from that of Onumah et al., (2013) who observed that farmers with a higher level of education were more inefficient or less efficient in production.

Another important variable that was found to significantly and negatively influence farmers' technical, allocative and economic inefficiencies was the use of climate smart adaptation strategies. The results from the three models as presented in Table 3 show that adopting more climate smart adaptation technologies increases the likelihood of cocoa farmers being more technically, allocatively, and economically efficient in production. That is, a higher climate smart adaptation drive among farmers makes them less inefficient in production. This finding is revealing, pointing to the significance of climate smart adaptation in the presence of the increasing trend of climate change and its adverse consequences on cocoa production. The observed significant impact of climate smart adaptation on farm-level efficiency improvement among cocoa lay credence to other study findings that observed that the adoption of climate smart adaptation technologies enhances farm-level productivity and performance of farmers in Ghana (see, for example, Adzawla & Alhassan, 2021; Issahaku & Abdulai, 2020; Mzyece & Ng'ombe, 2021). It is generally accepted that credit is an important factor when it comes to production due to its impact on production efficiency. Studies have reported that access to credit accounts for variation in farm-level efficiency among farmers (for example, Inkoom & Micah, 2017; Onumah et al., 2013). To validate this, we tested the impact of credit access on cocoa farmers' technical, allocative and economic efficiencies. From the three model results as presented in Table 2, we observed that access to credit has a significant and negative impact on the technical, allocative, and economic inefficiencies among cocoa farmers. This implies that having access to external credit facilities increases the likelihood of cocoa farmers attaining a higher level of technical efficiency, allocative efficiency, and economic efficiency. This could largely be attributed to the enhanced liquidity preference that access to credit presents to farmers, facilitating timely production decision-making and operational activities. The observed finding of credit access calls for the development of appropriate credit facilities for farmers and the reengineering of existing credit conditions by banks to make it more flexible for farmers to access credit to fund their farm business. In addition, we observed that farm size and farm labour both significantly accounted for the observed inefficiency variation among cocoa farmers. In particular, land size had a significant negative impact on the economic, technical, and allocative inefficiencies among farmers. This suggests that an increase in farm size tends to reduce the level of inefficiencies among farmers. hence it can be concluded that farmers with large farm sizes were more economically, technically, and allocatively efficient than their counter. On the contrary, farm labour was found to increase the level of economic, technical, and allocative inefficiencies among farmers. this could imply that there was possible misallocation as well as ineffective deployment of farm labour use on the cocoa farmers. The observed impact of farm size and farm labour use on farm-level efficiency is found to be consistent with that of Orisasona et al, (2019) who observed that whereas farm size positively impacts the input use efficiency, farm labour negatively impacts the level of input efficiency among cocoa farmers in Nigeria.

Conclusions and Policy Implications

Our paper considered the Efficiency-Effect Stochastic Frontier Analysis and the Tobit regression analysis to estimate cocoa farmers' farm-level technical, allocative, and economic efficiencies and their driving factors. The stochastic production results showed that the production function was monotonically increasing for labour, fertilizer, and capital inputs except for agrochemical input and that the observed productivity increases with more than the proportionate increases in the level of the aggregate inputs. In addition, the cost frontier model revealed that the cost function was monotonically non-decreasing for labour, capital, and fertilizer inputs except for agrochemical and that achieving a cost minimisation of one per cent increases the output quantity of cocoa significantly. Given this, by ensuring minimal input combination and effective cost-minimising production strategies, farmers could significantly maximise their utility of achieving higher productivity and profit. Policy intervention can therefore be framed to provide extensive education that provides appropriate field-level training to farmers on how to combine their input resources efficiently, using minimum input at the least cost possible to obtain maximum output. The results show that cocoa farmers, in general, exhibited a significant level of technical, allocative, and economic inefficiencies. The efficiency estimates revealed that cocoa farmers were fully not efficient in terms of their technical efficiency, allocative efficiency, and economic efficiency levels. This means that with the existing technology, farmers were operating far below their optimum potential, hence the need for stringent effort to build farmers' ability to generate maximum productivity without necessarily providing them with new technologies. Again, by engaging farmers in efficient and effective farm management and best agronomic practices, the cocoa productivity of farmers can significantly be increased at the least cost possible. Having established that farmers were not fully efficient in production, suggesting a gab, it became necessary to find out the driving forces of the observed efficiency differentials among the farmers. From the analysis of determinants of economic, technical, and allocative inefficiencies, we identified that key significant drivers of farm-level (in)efficiencies differentials include sex, household size, educational level, years of farming experience, frequency of extension contact, quality of extension received, use of climate smart adaptation technologies, farm size, farm labour and access to credit facilities. From this, cocoa extension service providers must ensure that they render frequent extension services which will help ensure access to timely technical information and identification and redress of farmers' problems. Again, our finding supports the position that by providing quality extension service delivery to farmers, the derived service utility which is a function of service quality will generate higher confidence and trust in farmers, influencing them to efficiently utilise the technological information and advice delivered to them. We further recommend that the government working with the relevant banking institutions and cocoa institutional authorities develop appropriate credit schemes for cocoa farmers to increase their liquidity preference in production. We further proposed that efforts be made by the government and other socio-cultural institutions to appropriately change the socio-cultural and economic factors that hinder the productivity of female cocoa farmers. Given that education significantly explains farm-level efficiency differential among cocoa farmers, we recommend to the Ghana Cocoa Board (COCOBOARD) to enhance and improve upon its extension education and farmer field school initiatives as well as develop some kind of adult education model for the less endowed cocoa farmer to help bring them up to speed in terms of educational abilities.

References

Abdulai, S., Nkegbe, P. K. & Donkor, S. A. (2017). Assessing the economic efficiency of maize production in Northern Ghana. Ghana Journal of Development Studies, 14(1), 123-145.

Adzawla, W. & Alhassan, H. (2021). Effects of climate adaptation on technical efficiency of maize production in Northern Ghana. Agricultural and Food Economics, 9(1), 1-18.

Aigner, D. J., Lovell, C. K. & Schmidt, P. (1977). Formation and estimation of stochastic frontier production function models. Journal of Econometrics, 6, 21-37.

Aneani, F., Anchirinah, V. M., Asamoah, M. & Owusu-Ansah, F. (2011). Analysis of economic efficiency in cocoa production in Ghana. African Journal of Food, Agriculture, Nutrition and Development, 11(1), 4507 - 4526.

Battese, G. E. & Corra, G.S. (1977). Estimation of a production function model with applied to the Pastoral Zone of Eastern Australia. Australian Journal of Agricultural Economics, 21, 169-179.

Battese, G.E. & Coelli, T.J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20, 325–332.

Besseah, F. A. & Kim, S. (2014). Technical efficiency of cocoa farmers in Ghana. Journal of Rural Development/Nongchon-Gyeongje, 37(1071-2016-86952), 159-182.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. Springer Science & Business Media.

Danso-Abbeam, G, Baiyegunhi, L. L. S. & Ojo, T. O., (2020). Gender differentials in technical efficiency of Ghanaian cocoa farmers. Heliyon, 6(5), 1-11.

Danso-Abbeam, G. & Baiyegunhi, L. L. S. (2020). Do farm-level technical efficiency and welfare complement each other? Insight from Ghana's cocoa industry. Journal of Economic Structures, 9 (23), 1 – 15.

Danso-Abbeam, G., Aidoo, R. & Ohene-Yankyera, K. A. K. (2012). Technical efficiency in Ghana's cocoa industry: evidence from Bibiani-Anhwiaso-Bekwai District. Journal of Development and Agricultural Economics, 4(10), 287-294.

Dharmendra, S. & Bashir, A. F. (2015). Technical efficiency and its determinants: an empirical study on banking sector of Oman. Problems and Perspectives in Management, 13(1), 168-175.

Djalilov, K. & Piesse, J. (2014). The Determinants of Bank Efficiency in Central Asia. Corporate Ownership and Control, 12(1), 656-670.

Farrell, M. J. (1957). The measurement of productivity efficiency. Journal of Royal Statistical Society Series A, 120(3), 253-81.

Ghana Cocoa Board [COCOBOD] (2019). Cocoa production in Ghana. Accra: Ghana Cocoa Board. Retrieve from https://www.cocobod.gh

Ghana Cocoa Board [COCOBOD] and Forests Initiative. (2017). Sustainable cocoa production. Accra: COCOBOB and Forest Initiatives.

Gong, T. C., Battese, G. E. & Villano, R. A. (2019). Family farms plus cooperatives in China: Technical efficiency in crop production. Journal of Asian Economics, 64, 101-129.

Greene, W. H. (2007). The econometric approach to efficiency analysis. Oxford: Oxford University Press.

Gwahula, R. (2013). Bank-Specific, Industry Specific and macroeconomic determinants of bank Efficiency in Tanzania: A two-stage analysis. Journal of Business Management, 5(3), 142-154.

Heathfield, D. F. (2016). An introduction to cost and production functions. New York: Macmillan International Higher Education.

Henningsen, A. (2020). Introduction to econometric production analysis with R. Copenhagen: University of Copenhagen.

Inkoom, E. W. & Micah, J. A. (2017). Estimating Economic Efficiency of Mango Production in Ghana. ADRRI Journal of agriculture and food sciences, 3(7), 29-46.

Inkoom, E. W., Dadzie, S. K. N. & Ndebugri, J. (2020). Promoting improved agricultural technologies to increase smallholder farm production efficiency: Ghanaian study of cassava farmers. International Journal of Food and Agricultural Economics, 8 (3), 271 – 294.

Issahaku, G. & Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural and Resource Economics, 64(2), 396-420.

Khalad, M. S. & Mazila, M. Y. (2014). Efficiency and Determinants in Libyan Banking. International Journal of Business and Social Science, 5(5), 156-168.

Kumbhakar, S. C. (1997). Modelling allocative inefficiency in a translog cost function and cost-share equation: an exact relationship. Journal of Econometrics, 76(1-2), 351-356.

Kumbhakar, S. C. & Lovell, C. K. (2003). Stochastic frontier analysis. Cambridge: Cambridge University Press.

Kumbhakar, S. C., Parmeter, C. F. & Zelenyuk, V. (2020). Stochastic frontier analysis: Foundations and advances I. Handbook of Production Economics, 1-39.

Kyei, L., Foli, G. & Ankoh, J. (2011). Analysis of factors affecting the technical efficiency of cocoa farmers in the Offinso district-Ashanti region, Ghana. American Journal of Social and Management Sciences, 2(2), 208-216.

Meeusen, W. & Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed errors. International Economic Review, 18(2), 435 - 444.

Miao, C., Fang, D., Sun, L., & Luo, Q. (2017). Natural resource utilization efficiency under the influence of green technological innovation. Resources, Conservation and Recycling, 126, 153-161.

Mzyece, A. & Ng'ombe, J. N. (2021). Crop diversification improves technical efficiency and reduces income variability in Northern Ghana. Journal of Agriculture and Food Research, 5, 100-162.

O'Donnell, C. J. (2018). Productivity and efficiency analysis: An economic approach to measuring and explaining managerial performance. Gateway East, Singapore: Springer Nature Singapore Press Ltd.

Ogunya, L. & Tijani, A. (2022). Economic Efficiency of Organic Farming Adoption by Cocoa Farmers in Southwest, Nigeria. Journal of Agricultural Economics, 7(1), 36-48.

Onumah, E. E., Brümmer, B. & Hörstgen-Schwark, G. (2010). Elements which delimitate technical efficiency of fish farms in Ghana. Journal of the World Aquaculture Society, 41(4), 506-518.

Onumah, J. A., Onumah, E. E., Al-Hassan, R. M., & Bruemmer, B. (2013). Meta-frontier analysis of organic and conventional cocoa production in Ghana. Agricultural Economics- Czech, 6, 271 – 280.

Orisasona, T. M., Taiwo, O., Agbebaku, E. E. O., Oluyole, K. A., Williams, O. A. & Abdulkarim, I. F. (2019). Input Use Efficiency of Cocoa Production among Small Scale Farmers in Ondo State. Journal of Agriculture and Ecology Research International, 16(4), 1-8.

Sauer, J., Frohberg, K. & Hockmann, H. (2006). Stochastic efficiency measurement: the curse of theoretical consistency. Journal of Applied Economics, 9(1), 139-165.

Schmidt, P. (2011). One-step and two-step estimation in SFA models. Journal of Productivity Analysis, 36(2): 201-203.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. Econometrica, 26(1), 24-26.

Wang, H.-J. (2002). Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. Journal of Productivity Analysis, 18(3), 241-253.

Wang, H. J. & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. Journal of Productivity Analysis, 18(2), 129-144.

Wheat, P., Stead, A. D. & Greene, W. H. (2019). Robust stochastic frontier analysis: A Student's half-normal model with application to highway maintenance costs in England. Journal of Productivity Analysis, 51(1), 21-38.

Wollie, G., Zemedu, L. & Tegegn, B. (2018). Economic efficiency of smallholder farmers in barley production in Meket district, Ethiopia. Journal of development and agricultural Economics, 10(10), 328-338.

Yamane, T. (1967). Statistics, an introductory Analysis (2nd Edition). New York: Horper and Row.

.