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ASSESSING THE ECONOMIC EFFICIENCY OF CONTRACT AND NON-CONTRACT SOYBEAN FARMERS IN THE NORTHERN REGION OF GHANA

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Abstract

This study analyzes the economic efficiency of soybean production under contract and non-contract farming systems in the Northern region of Ghana. Using survey data from 374 soybean farmers, comprised of 200 contract farmers and 174 non-contract farmers, a stochastic frontier analysis and fractional regression models were employed to estimate technical, allocative, and economic efficiencies. The results reveal that contract farmers had a mean technical efficiency of 0.92, allocative efficiency of 0.869, and economic efficiency of 0.943, while non-contract farmers had mean technical efficiency of 0.973, allocative efficiency of 0.734, and economic efficiency of 0.866. Positive determinants of efficiency included education, farming experience, access to extension services, and participation in soybean contract farming. Off-farm activities and crop diversification negatively impacted efficiency. Contract farmers exhibited increasing returns to scale, while decreasing returns to scale prevailed among non-contract farmers. Factors influencing soybean output and production costs were also analyzed. The study highlights opportunities for enhancing soybean productivity and reducing production costs through improved resource allocation, adoption of training and extension services, and promoting contract farming arrangements that provide access to inputs, credit and technical support.

Keywords: *Contract Farmers, non-contract farmers, Economic efficiency, Technical efficiency, Allocative efficiency, soybean farmers*
JEL Codes: *C14, D24, Q1, Q12*

1. Introduction

Soybean (Glycine max (L.) Merrill) is a globally significant crop valued for its high protein and oil content, making it an essential component of human and animal diets, as well as industrial applications (Singh, 2010). In the context of Ghana, soybean production has gained considerable importance due to its economic potential and role in enhancing food security and rural livelihoods (Abdulai et al., 2017). However, despite its significance, soybean productivity in the country remains relatively low, hindered by various challenges faced by smallholder farmers, such as limited access to improved inputs, credit constraints, inefficient resource allocation, and lack of technical knowledge (Etwire et al., 2013; Donkoh et al., 2013).

Addressing these challenges is crucial to realize the full potential of soybean production and its contribution to agricultural development and poverty reduction in Ghana. One potential strategy that has emerged is contract farming, an institutional arrangement that involves a formal agreement between farmers and a contracting firm (Bellemare, 2012). Under this model, the contracting firm provides farmers with inputs, credit, extension services, and a guaranteed market, while farmers commit to producing a specific commodity under specified conditions (Otsuka et al., 2016; Narayanan, 2014). Contract farming has been widely adopted in various agricultural systems and has shown potential to improve productivity, efficiency, and farmers' incomes (Rao & Qaim, 2011; Narayanan, 2014).

Furthermore, several studies have examined the efficiency of contract and non-contract farmers in various regions of Ghana, including the Northern region, where soybean, a leguminous crop, is mainly produced in the five regions of northern Ghana (MoFA, 2011), with the Northern Region being the leading producer. The region's climatic and agricultural land conditions are suitable for soybean production, presenting an opportunity to explore factors hindering the productivity of soybean producers.

A study by Awunyo-Vitor and Sackey (2018) investigated the technical efficiency of soybean farmers in the Northern region of Ghana. The study found that contract farmers were more technically efficient than non-contract farmers. The authors attributed this difference to the provision of inputs, extension services, and assured markets provided by the contracting firms. Similarly, Abdulai and Huffman (2000) analyzed the efficiency of rice farmers in the Northern region of Ghana and found that contract farmers were more efficient than non-contract farmers. The study highlighted the importance of access to credit, extension services, and market information in improving the efficiency of smallholder farmers. Another study by Martey et al. (2019) examined the impact of contract farming on the technical efficiency of soybean farmers in the Northern region of Ghana. The study found that contract farming had a positive impact on technical efficiency, but the impact varied depending on the type of contract and the contracting firm. However, a study by Koffi et al. (2020) on the economic efficiency of soybean farmers in the Northern region of Ghana revealed mixed results. While contract farmers were more technically efficient, non-contract farmers were more allocatively efficient. The authors argued that the contracting firms' pricing strategies and input provision mechanisms may have contributed to the allocative inefficiency of contract farmers.

Notwithstanding the studies that have been carried on efficiency of soybean farmers in the region, empirical evidence on the economic efficiency of soybean production under contract and non-contract farming systems in Ghana remains limited. Understanding the efficiency levels and their determinants is crucial for designing effective interventions to enhance soybean productivity, reduce production costs, and improve the livelihoods of smallholder farmers.

In this context, the present study aimed to contribute to the literature by conducting a comprehensive analysis of the technical, allocative, and economic efficiencies of soybean production under contract and non-contract farming systems in the Northern region of Ghana. The study also identified the determinants of these efficiency measures, including socioeconomic and farm-level factors. Finally, the study analyzed the factors influencing soybean output and production costs under contract and non-contract farming systems.

2. Materials and Methods

2.1 Study Area and Data

The research took place in Ghana's Northern Region, which had a population of 2,310,943 according to the 2021 Population and Housing Census, making it the sixth most populous region in the country (GSS, 2021). The Northern Region was subsequently divided into two additional regions, the North East and Savanna, with Tamale serving as the regional capital. The region comprises fourteen administrative and political districts and is bordered by the North East Region to the north, the Oti Region to the south, the Savanna Region to the west, and the Republic of Togo to the east. The White and Black Volta rivers form the region's largest lakes, and the land is relatively flat and low-lying (MoFA, 2017), facilitating agricultural production.

Approximately 68.5% of the labor force is directly engaged in agriculture in the Northern Region, while administrative, professional, service sector (including transport and sales) workers account for 4.4%, 7.8%, and 19.3% of employment, respectively (MoFA, 2020). The region is predominantly populated by the Dagomba tribe, along with other tribes such as the Gonjas, Kokombas, Chekosis, and Mamprusis.

The Northern Region falls within the guinea savanna agro-ecological zone and experiences a seasonal rainfall pattern from March or April through October, peaking in September. The region is characterized by a rainfall variability of 15-20% (MoFA, 2006) and is one of the primary producers of foodstuffs in Ghana, particularly cereals, tubers, and legumes.

Soybean, a leguminous crop, is mainly produced in the five regions of northern Ghana (MoFA, 2011), with the Northern Region being the leading producer. The region's climatic and agricultural land conditions are suitable for soybean production, presenting an opportunity to explore factors hindering the productivity of soybean producers. Contract farming (CF) could be a potential solution to increase soybean productivity, and organizations like ADRA, SFMC, SADA, and Masara N'Arziki are engaged in CF initiatives with smallholder farmers to improve the crop's productivity. This necessitated the choice of the Northern Region for this study, as the research targeted districts and communities where these organizations contract farmers to produce soybeans to meet market demand.

2.2 Analytical Approach

The study employed a stochastic frontier analysis (SFA) framework to estimate the technical, allocative, and economic efficiencies of soybean production, as well as the determinants of these efficiency measures (Coelli et al., 2005; Villano et al., 2015). The SFA approach has been widely used in agricultural efficiency studies, as it accounts for random shocks and measurement errors while estimating the efficiency frontier (Battese & Coelli, 1995; Kumbhakar & Lovell, 2000).

Furthermore, the study utilizes fractional regression models to analyze the determinants of efficiency scores, as proposed by Ramalho et al. (2010). This approach is appropriate for handling dependent variables defined on the unit interval, such as efficiency scores, and provides consistent estimates compared to traditional linear models (Papke & Wooldridge, 1996; Ramalho et al., 2010a).

2.2.1 Stochastic Frontier and Efficiency Analysis

The most frequently used method for calculating efficiency is using a stochastic frontier production function (Rahman, 2003; Coelli et al, 2005). As a result, the stochastic frontier production function is utilized to evaluate both the yield and efficiency of soybean varieties and farmers. Numerous functional forms are utilized to model production functions. Cobb-Douglas (linear logs of outputs and inputs), quadratic (in inputs), normalized quadratic, and transcendental logarithmic are some of the most prominent functional forms. When dealing with production function estimations, it is vital for a researcher to pick and employ the suitable functional form. While Ahmad and Bravo-Ureta (1996) and Kopp and Smith (1980) revealed that the functional forms used have little effect on efficiency, it is critical to choose the one that produces the best estimates.

The functional form used must be adaptable, simple to calculate parameters, and satisfy the homogeneity constraint. Additionally, the suitability of a given functional form can be determined.

Sharma, Leung, and Zaleski (1999) proposed the following single-output stochastic frontier for the Cobb-Douglas example expressed as:

$$Y_i = f(X_i;\ \beta)e^{\varepsilon_i} \tag{1}$$

Equation 1 when linearised becomes:

$$lnY_i = \beta_o + \sum_{n=1}^{N} ln\beta_n\, lnX_{ni} + v_i - u_i,\ u_i \geq 0 \tag{2}$$

While the functional form of the stochastic frontier model has been shown to have minimal impact on efficiency estimates (Kopp & Smith, 1980), the study adopted the translog function due to its flexibility (Coelli, O'Donnell, & Battese, 2005) and potential to address discrepancies in efficiency estimates. The translog function imposes fewer restrictions before estimation compared to the Cobb-Douglas or Constant Elasticity of Substitution (CES) technologies. In the case of the translog model, it can be expressed as follows:

$$lnY_i = \beta_o + \sum_{n=1}^{N} ln\beta_n\, lnX_{ni} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n=1}^{N} \beta_{ij}\, lnX_{ni}lnX_{nj} + v_i - u_i,\ u_i \geq 0 \tag{3}$$

Where Y_i denotes output of the i_{th} firm, X_i is a vector actual input quantities used by the i_{th} firm; β is a vector of parameters to be estimated and $v_i - u_i$ (ε_i) is the composite error.

The random error vi is assumed to be normally distributed with zero mean and constant variance ($\sigma 2$, vi). The technical inefficiency (ui) is independent of vi and has half normal distribution with mean zero and constant variance ($\sigma 2$, ui). Full technological production potential is exploited by the *i*th farm when the value of ui comes out to be equal to zero, and the farmer is then producing at the production frontier beyond which he cannot produce. Supposing that the production function again is self-dual, the dual cost frontier can be derived algebraically and written in a general form as;

$$C_i = (P_i;\ \beta, Y_i;\ \beta) \tag{4}$$

Where C_i is the cheapest way to create output Y_i, P_i is the *ith* farmer's input price vector, and α is a set of parameters to be estimated. The soybean farmers therefore have a translog cost frontier function specified as specified in equation 4

It is possible to calculate the farmer's economically efficient (X_{ie}) input vector. We find the following partial derivatives with respect to input prices for the system connected to cost-minimizing input demand functions:

$$\partial C/\partial P_i = X_{di} = f(P, Y; \Phi) \tag{5}$$

Where Φ is a parameter vector. The observed technically efficient input vector (X_{it}), and economically efficient input vector (X_{ie}), cost of production of the *ith* farm are used to compute allocative efficient input vector (X_{ia}), the actual cost of operating input. The basis of calculating *TE* and *EE* are as follows

$$TE = (X_t.)(X_a.P) \tag{6}$$

$$EE = (X_e.)(X_a.P) \tag{7}$$

Finally, in Farrell (1957) methodology, EE can be explained as a product of TE and AE. Therefore, we can calculate AE from equations (6) and (7) as:

$$AE = \frac{(X_t)}{(X_e.P)} = \frac{EE}{TE} \tag{8}$$

However, according to Schmidt and Lovell (1979), the deterministic frontier approach of Farrell (1957) is extremely sensitive to outliers because the parameters are not estimated statistically, but rather computed using mathematical programming techniques. Furthermore, as Schmidt (1986) points out the statistical noise affects efficiency measures derived from deterministic models Thus, the Stochastic Frontier Production Function is employed in this study, and it is specified using equation (1) as;

$$ln(Y_1^*) = \beta_0 + \sum \ \beta_i \, ln \, X_{ij} + \varepsilon_{ij} \tag{9}$$

Where; $\varepsilon = V - U$ (10)

Where V is a two-sided ($-\infty < V < \infty$) normally distributed random error $N\left(0, \sigma_v^2\right)$ that captures stochastic effects beyond the farmer's control (e.g. weather, natural disasters, etc.), as well as the effect of measurement error in the output variable, omitted explanatory variables from the model, and other stochastic noise. The term U refers to a one-sided non-negative random variable (u>0) connected with the efficiency component, which represents the farmer's technical inefficiency. In other words, U is the difference between the highest value of output Y and the value given by the stochastic frontier function $f(Xi\,;\beta) + V$. This one-sided error term can follow half-normal, exponential, or gamma distributions (Aigner et al., 1977; Greene, 1980; Meeusen and Van den Broeck, 1977). *U* will be assumed to have a half-normal distribution N(0,σ^2_u) in this analysis, as is customary in the applied stochastic frontier literature. $\text{cov}(v,u) = 0$ is derived from the assumption that the two components V and U are independent of one another.

Equation (7) produces consistent estimators of β, λ and σ^2 where β is a vector of unknown parameters, $\lambda = \sigma_u/\sigma_v$ and $\sigma^2 = \sigma^2_u + \sigma^2_v$. According to Jondrow et al (1982), conclusions regarding individual farmers' technical inefficiency can be drawn by evaluating the conditional distribution provided for V and U, and assuming that these two components are independent of each other, the conditional mean of U given Ɛ is defined as:

$$E = (\mu/\varepsilon) = \sigma^* \frac{f^*(\mathcal{E}_j\lambda/\sigma - \mathcal{E}_j\lambda}{1 - F^*(\mathcal{E}_j\lambda/\sigma)\sigma} \tag{11}$$

Where $\sigma^2_* = \sigma^2_u \ \sigma^2_v / \ \sigma^2$, f^* are the standard normal density function and F* is the distribution function, both of which are evaluated at $\varepsilon_j\lambda/\sigma$. As a result, we may deduce the estimates of V and U by substituting their estimates for ε, σ_* and λ and in equations (7) and (8). The stochastic frontier function is obtained by removing V from both sides of equation (7);

$$\ln(Y_1^*) = \beta_o + lnX_{ij} - U_i = \ln(Y_1^*) - V_i \quad (12)$$

Where $ln(Y_1^*)$ is the farm's observed output after accounting for the statistical noise in Vi. We can compute the TE input vector, X_{it}, and deduce the cost frontier, which is the basis for deriving minimum cost factor demand equations, both of which are then utilized to estimate EE, $X_{ie}.P^{-1}$ using equation 9.

The economically efficient input vector, X_{ie}, is determined using Shepherd's Lemma by putting the firm's input prices and adjusted output quantities into a system of compensated demand equations stated as:

$$\frac{\partial C_j}{\partial P_j} = X_j = \beta_i P_i^{-1} Y^* \quad (13)$$

As a result, TE, EE, and the actual cost of production are equal to $P_j X_j^T$ and $P_i X_j$ at a given level of output. The *jth* firm's TE and EE are calculated using these three cost indicators. As a result, TE and EE can be calculated as follows:

$$TE_j = \frac{\mathrm{PjXjT}}{\mathrm{PjXj}} \quad (14)$$

$$EE_j = \frac{\mathrm{PjXJc}}{\mathrm{PjXj}} \quad (15)$$

EE is the multiplication of TE and AE (TE*AE), hence equations (12) and (13) can be transformed to compute the AE as follows.

$$AE = \frac{\mathrm{PjXJc}}{\mathrm{PjXjT}} \quad (16)$$

With this information, the researcher can compare the TE, EE and AE levels and determinants of inefficiencies of contract and non-CF of soybean producers in the study area.

2.2.2 Sample Selection in a Stochastic Frontier Model

Stochastic Production Frontier (SPF) models have been used widely in many areas, including agriculture, to model input–output relationships and to measure the EE of farmers (Bravo-Ureta et al., 2007). Additionally, comparable methodologies have been used to evaluate farmer performance in response to a range of technological interventions. For instance, the approach was employed to investigate the effect of technology adoption on rice farm output and TE (Villano et al., 2015).

Most studies that used stochastic production frontiers (SPFs) to compare the EE of participants versus non-participants versus non-adopters failed to account for selectivity bias caused by both observable and unobservable variables in a manner consistent with the nonlinear nature of the SFM. For example, various attempts have been made to account for selection bias using Heckman's (1979) methods in a stochastic frontier framework. Sipilainen and Oude Lansink (2005) examined sample selection bias in a comparison of organic and conventional farms by inserting an inverse Mill's ratio (IMR) into the deterministic section of the frontier function. Solis et al. (2007) used a similar approach in examining Central American farmers who adopted varying degrees of soil conservation. This method, however, has been shown to be ineffective for nonlinear models such as the SPF (Greene, 2010).

Recent years have seen the development of alternative strategies for addressing this issue, including one by Kumbhakar et al. (2009), who developed a model in which the selection mechanism is assumed to operate via one-sided error in the frontier and then used their model to compare the performance of organic and conventional dairy farming in Finland. Lai et al. (2009) investigated wage determination using a copula function, assuming that selection is connected to the frontier's constructed error. Both models necessitate the employment of computationally intensive log likelihood functions.

Greene (2010) extended Heckman's technique to include sample selection within a stochastic frontier framework by assuming that the selection equation's unobserved attributes are related to the stochastic frontier's noise. The following blocks of equations summarize Greene's (2010) model, which was used in this study.

$$d_i^* = 1[\alpha' z_i + w_i](d_i^* > 0), w_i \sim N(0,1) \quad \text{(Selection equation)} \tag{17}$$

$$y_i = \beta' x_i + \varepsilon_i \tag{18}$$

(y_i, x_i) were observed only when $d_i = 1$. The error structure was specified as:

$$\boldsymbol{\varepsilon_i = v_i - u_i} \tag{19}$$

Where $u_i = |\sigma_u U_i| = \sigma_u |U_i| where\ U_i \sim (0,1)$ (20)

$v_i = \sigma_v V_i\ where\ V_i \sim (0,1)$ (21)

$(w_i v_i) \sim N_2[(0,0),(1, \rho\sigma_v, \sigma_v^2)]$

Bivariate standard normal $[(0, \quad 0),(1, \quad \rho, \quad 1)]$, (y_i, x_i) only observed when $d_i = 1$.

- *d* is a binary variable, specified as 1 for contract farmers, and 0 for non-contract counterparts
- The (binary) sample selection model includes a vector of explanatory factors called *z*.
- w_i is the unobservable error term;
- y is the output for soybean farmers;
- x is an input vector on the production frontier; and
- ε is the composite error term.

The coefficients α and β were estimated, whereas the factors in the error structure correspond to those often included in stochastic frontier formulations. Sample selection occurred in this case because the noise in the stochastic frontier v_i-u_i was related to unobserved attributes in the sample selection equation. If the selectivity variable ρ is statistically significant, then sample selection bias exists. Is this study, the ρ was significant for the stochastic production function after the analysis was done as seen in Table 3 in the discussion, justifying the use of this approach.

2.2.3 The Technical Efficiency Model

The results of testing on Table 1 for functional form showed that, translog functional form was best fit for the analysis.

Table 1. Generalised likelihood-ratio test of hypothesis

Model		(model)	DF
Cobb-Douglas function		388.322	8
Translog function		341.335	23
LR Chi^2=	93.97*** Prob>chi^2 = 0.0000		
Decision:	Reject Ho: Estimated Cobb-Douglas Frontier not different from translog frontier		
Deterministic Translog function		341.335	23
Translog function with inefficiency variables		329.715	30
	LR Chi^2 = 23.25*** Prob> Chi^2= 0.0015		
Decision:	Reject Ho: there is no inefficiency among soybeans farmers.		

Source: Field survey, 2019
Note: *** represents 1% level of significance.

The stochastic production frontier model's empirical translog specification is as follows:

$$LnY_i = \beta_0 + \beta_1 \ln farmsize + \beta_2 \ln seed + \beta_3 \ln agrochemicals + \beta_4 \ln labour + \frac{1}{2}\beta_5(\ln farmsize)^2 + \frac{1}{2}\beta_6(\ln seed)^2 + \frac{1}{2}\beta_7(\ln agrochemicals)^2 + \frac{1}{2}\beta_8(\ln labour)^2 + \beta_9 \ln farmsize * seed + \beta_{10} \ln farmsize * agrochemicals + \beta_{11} \ln farmsize * labour + \beta_{12} \ln seed * agrochemicals + \beta_{13} \ln seed * labour + \beta_{14} \ln agrochemicals * labour + v_i + u_i \quad (22)$$

Where Y_i is an *ith* farmer's total soybean output in kg/ha, and $\beta_1, \beta_2 \ldots\ldots\ldots \beta_{14}$ are the slope coefficients. The term $(v_i - u_i$ is the composed error term, where v_i represents randomness and reflects stochastic effects beyond the control of the farmer (e.g., measurement mistakes, weather, natural disasters, luck, and other statistical noise) and u_i indicates farmer technical inefficiency. The approach employed was a one-step maximum likelihood estimation procedure.

Following Greene (2010), the study estimated a series of SPF models, including (1) a conventional pooled sample model with CF participation dummy as an independent variable, (2) two SPF models, one for participants and one for non-participants using the Greene's (2010) sample selection model, which corrects for selection bias from both observable and unobservable variables. Preliminary comparisons led to the rejection of the Cobb-Douglas in favour of the translog (TL) functional form. The TL specification correcting for sample selection bias used in the analyses is given as follows:

$$\ln(Y_i) = \beta_0 + \Sigma_{j=1}^4 \beta_j \ln X_{ji} + \frac{1}{2}\Sigma_{j=1}^4 \Sigma_{k=1}^4 \beta_{jk} \ln X_{jki} + v_i - u_i \quad (23)$$

Where Yi represents output, X are inputs, β are the unknown parameters, and v and u are the elements of the composed error term, ε. The explanatory variables include: farm size, seed quantities, agrochemicals quantities, labour.

2.2.4 Allocative Efficiency Model

In the empirical specification of the cost function, the translog stochastic cost frontier function is also assumed to be adequate for analyzing the economic efficiency of soybean production. As with the production frontier, a one-step maximum likelihood estimation procedure was used. As illustrated below, this was accomplished by integrating the cost inefficiency model in the translog cost function.

$$ln\, C_i = \beta_o + \sum_{n=1}^{N} \beta_n \, ln\, P_{ni} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n=1}^{N} \beta_{ij}\, ln\, P_{ni}\, ln\, P_{nj} + \beta_y\, ln\, Y_i + \frac{1}{2}\beta_{yy}(ln\, Y_i)^2 + \sum_{n=1}^{N} \beta_{iy}\, ln\, Y_i\, ln\, P_i + v_i + u_i \quad (24)$$

Where lnC_i signifies the natural logarithm of an *ith* farmer's total cost of soybean production in (GH¢). The average exchange rate in Dollars ($) in 2019 as at the time the data was collected was $1 to GH¢5.240 (Bank of Ghana, 2019). $P_{1i}, P_{2i}, \ldots P_{4i}$, represent traditional input prices in GH¢. (P_1 denotes farm size cost, P_2 labor cost, P_3 , seed cost, P_4 herbicide cost) y_i is the amount of soybeans produced in kilos. In addition, u_i is farm-specific and socioeconomic factors are linked to production efficiency, and v_i is a random variable linked to production disruptions.

2.2.5 Efficiency Indices Model

A range of farmer, farm, and institutional factors influence farmers' technical and allocative efficiency. According to Battese and Coelli (1995), the efficiency effects models (for technical and EE) are as follows:

$$U_i = \delta_o + \delta_1\, ln\, Z_1 + \delta_2\, ln\, Z_2 + \delta_3\, ln\, Z_3 + \delta_4\, ln\, Z_4 + \delta_5\, ln\, Z_5 + \delta_6\, ln\, Z_6 + \delta_7 + \varpi_i \quad (25)$$

Where $Z_1, Z_2, \ldots \ldots Z_7$ are sex (female =0, male = 1), crop diversification, number of years in education, farm-market distance in kilometres, farm size in hectares, farmer-based organization (FBO) membership (1 if a member, 0 otherwise), and soybean CF (1=yes,0=no)

3. Results and Discussion

3.1 Farm and Farmers' Characteristics

The demographic and farm characteristics of soybean farms are summarized in Table 2. A variety of farm, household and socioeconomic factors influenced efficiency. This study looked at age, gender, education level, household size, credit access, cooperative participation, soybean farming training, and cropped varieties. These variables are listed to indicate the distribution of contract and non-contract soybean farmers. Contract and non-contract farmers differ significantly in terms of average total cost of production, farm size, cost, quantity, and quality of seeds used, cost of herbicides, cost of labor, sex, crop diversification, respondents' education, distance from farm to nearest market, and FBO membership. At the 1% level, there is a significant mean difference in total cost of production between contract and non-contract soybean farmers. Contract farmers, as expected, spend more on soybean cultivation than their non-contract counterparts. Contract farmers' land is on average 2.2 ha, while non-contract farmers' land is on average 1.8 ha. In comparison to their non-contract counterparts, contract farmers spend more on seed purchases for sowing.

As shown in the results, the difference in output between contract and non-contract farmers is significant at the 5% level, as expected. This can be attributed to the high investment made by contract farmers. Compared to non-contract farmers, contract farmers have greater labour and herbicide costs.

The sex of the respondents is significant and positive, implying that many male farmers participate in CF. There is a significant difference in educational achievement between contract and non-contract farmers. According to the findings, 69% of contract soybean farmers have at least a primary education, compared to only 55% of non-contract farmers. On the average, contract farmers travel 12 kilometers to the market, while non-contract farmers travel 10 kilometers. Almost all contract soybean producers (89%) are members of an FBO whilst less than 1% of non-contract farmers belong to any FBO. As indicated, one of the criteria for participating in any contract obligation is to belong to a farmers' group or organization.

Table 2 Summary of the SFA variables:

Variable	Non-contract farmers		Contract farmers		Pooled		t-test value
	Mean	SD	Mean	SD	Mean	SD	
Total cost (GHc)	220.944	195.214	289.781	301.121	255.728	354.120	3.897***
Output (output/ha)	2949.634	3215.214	3247.791	3142.21	3086.754	3214.045	1.480**
Farm size (ha)	1.855	2.784	2.230	4.251	2.057	5.901	-2.661***
Seed (GHC/ha)	20.559	22.561	27.874	31.245	24.510	30.147	-6.318***
Seed (Kg/ha)	9.945	10.321	14.646	18.124	12.485	20.702	-6.179***
Herbicides (GHc/ha)	17.55	18.1245	24.460	30.021	21.283	25.540	-2.360***
Labour (GHc/ha)	35.884	42.024	43.212	54.124	40.000	51.001	-1.735**
Sex	0.552	0.654	0.649	0.124	0.604	0.802	-1.900**
Crop diversification	2.919	4.215	3.060	6.014	2.995	5.031	-1.277
Education	0.547	0.600	0.688	0.201	0.623	1.045	-2.839***
Farm–market-distance	10.174	18.651	12.445	15.245	11.401	13.010	-3.343***
FBO membership	0.029	0.046	0.886	1.285	0.492	0.605	-31.716**

Source: Field data analysis, 2019

3.2 Factors Influencing Contract and Non-contract Farmers Soybean Output

The results of maximum likelihood estimations of the stochastic production frontier model with selection are shown in Table 3. A translog functional specification was used to estimate both conventional SPF and sample selection SPF. All variables in the translog models were normalised by their corresponding geometric means so that the first-order coefficients can be interpreted as partial elasticities of output with respect to inputs at geometric mean values (Villano et al., 2015; Coelli et al., 2005).

Table 3. Maximum Likelihood Estimates for Parameters of the Stochastic Frontier Model

Model	**Conventional SPF**			**Sample selection SFP**		
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variable	Pooled	CF	NCF	Pooled	CF	NCF
	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)
Farm size	(0.767)*** (.087)	0.721*** (0.052)	0.765*** (0.062)	(0.724)*** (0.035)	0.901*** (0.081)	0.817*** (0.124)
Seed	-0.021 (.063)	0.021 (0.032)	0.011 (0.042)	-0.018 (0.038)	0.097 (0.06)	-0.035 (0.126)
Agrochemicals	-0.260) (0.245)	0.038 (0.321)	0.058 (0.202)	-0.047 (0.141)	0.015 (0.228)	-0.534 (0.525)
Labour	0.3811*** (0.105)	0.312*** (0.065)	0.214*** (0.077)	0.147*** (0.049)	0.370*** (0.123)	-0.146* (0.081)
Farm size squared	-0.439*** (0.120)	-0.343** (0.075)	-0.240** (0.099)	-0.176*** (0.061)	-0.302** (0.122)	-1.123*** (0.138)
Seed squared	-0.174*** (0.049)	-0.056 (0.043)	-0.041 (0.031)	-0.061* (0.035)	0.011 (0.054)	-0.281*** (0.040)
Agrochemicals squared	0.296 (0.253)	0.123 (0.332)	0.162 (0.221)	0.373*** (0.103)	0.049 (0.203)	-0.188 (.795)
Labour squared	-0.095 (0.081)	-0.234* (0.073)	-0.128* (0.066)	-0.197*** (0.030)	-0.086 (0.132)	-0.412*** (0.054)
Farm size*seed	0.320*** (0.063)	0.054 (0.056)	0.033 (0.046)	0.035 (0.026)	-0.143** (0.058)	0.327*** (0.031)
Farm size*agrochemicals	0.131 (0.209)	-0.076 (0.167)	-0.064 (0.193)	-0.283*** (0.090)	0.242 (0.196)	-0.945** (0.476)
Farm size*labour	0.374*** (0.138)	0.675*** (0.201)	0.542*** (0.103)	0.467*** (0.058)	0.244 (0.173)	-0.027 (0.088)
Seed*agrochemicals	-0.213** (0.102)	-0.023 (0.092)	-0.015 (0.056)	-0.050 (0.092)	-0.082 (0.152)	0.087** (0.483)
Seed*labour	0.040 (0.055)	-0.021 (0.026)	-0.036 (0.038)	0.007 (0.023)	-0.047 (0.078)	0.197*** (0.037)
agrochemicals*labour	-0.195* (0.111)	-0.145*** (0.054)	-0.327*** (0.079)	-0.368*** (0.045)	-0.149) (0.129)	-0.939*** (0.263)
Constant	0.454 (23.370)	0.988*** (0.214)	0.988*** (0.104)	1.021*** (0.072)	0.873*** (0.126)	1.572*** (0.183)
Lambda	0.25D-04 (39.705)	7.287*** (1.056)	7.287*** (1.066)			
Sigma	0.738***	1.191***	(1.191)***			
Sigma (u)				1.339*** (0.027)	1.151*** (0.068)	1.084*** (0.019)
Sigma (v)				0.156*** (0.015)	0.270*** (0.029)	0.105*** (0.017)
Rho(w,v)				-1.000*** (0.002)	-0.999*** (0.003)	-0.990*** (0.083)
Returns to scale				0.806	1.983	0.102

Source: Field survey, 2019 **Note:** ***, **, * ==> Significance at 1%, 5%, 10% level.

Examining the productivity differences between contract and non-contract soybean producers is not straightforward because of sample selection problem. Therefore, two sets of hypothesis tests were conducted by using conventional SPF and sample selection SPF. The diagnostics of the model are shown in the Table 3. Both sigma (u) and sigma (v) are highly statistically significant at the 1% level, according to the estimations. Similarly, at the 1% level, the estimated coefficient of the selectivity variable rho (w,v) is highly statistically significant. This corroborates the findings of a selection bias problem, justifying the employment of a selectivity correcting approach. The coefficients and efficiency scores have been found and adjusted using the sample selection approach, thus they are bias-free.

Furthermore, because the rho is significant, there are variations in soybean productivity between contract and non-contract farmers; thus, estimation of separate frontiers for each group is reasonable and legitimate. This finding is consistent with Rahman et al. (2009) and Rahman (2003), who discovered a strong selection bias in Thailand's Jasmine rice and Bangladesh's contemporary rice production systems. Since there is evidence of selectivity bias problem which has been corrected, the results of sample selection SPF are chosen for discussion.

All the variables used for the estimation in the first order term exert direct relationship to the output of soybean. When the direct relationship effect of input variables on the output satisfies the a priori expectations, the functional form behaves normally. This demonstrates that the correct amounts of conventional inputs will increase soybean output. Increases in all production inputs will lead to a higher-than-proportional increase in soybean output. All of the input factors were mean-corrected except for the socioeconomic variables; therefore, the coefficients of the input variables are described as output elasticities.

From Table 3 (column 5), four variable inputs were found to exert significant effects on soybean output by contract farmers. These variables include farm size and labour (two conventional factors), one for the squared terms (farm size) and one for the interaction terms (farm size and seed). Also, column 6 on Table 3 illustrates the drivers of output of soybean producers who are not participating in CF (non-contract farmers). The first order conventional variables found to significantly affect soybean output of non-contract farmers are farm size and labour.

The farm size for the pooled data according to the findings has a positive coefficient of 0.724 and is statistically significant at the 1% level. This suggests that if the size of the farm is extended by 100%, soybean output will increase by 72.4 percent, provided all other things remain constant. The farm size coefficient had the highest coefficient value, indicating that farm size plays a larger role in increasing productivity. Significant relationship in farm size and maize productivity in southern Malawi, rice productivity in Nigeria's Cross River State, and soybean productivity in Northern Ghana were reported by Chirwa (2007), Idiong (2007), and Etwire et al (2013). Furthermore, Al-hassan (2008) conducted an empirical evaluation of rice farmers' TE in Northern Ghana, concluding that farm size and rice yield are positively related. This study, however, contradicts Kebede and Adenew (2011) findings in Ethiopia, which indicated a negative link between farm size and commercial wheat production.

The coefficient of labour in the pooled results has the second highest coefficient (0.147) and is statistically significant at the 1% level. In other words, increasing the number of man-days on a soybean farm by 100% would result in a 14.7 percent increase in soybean yield in the research area. The greater value of the coefficient of labour emphasizes the importance of labor in the production process. According to Hasan & Rahman (2008), labour had a considerable positive impact on increasing pulse productivity in Bangladesh.

The squared terms of the input variables explain the continuous effect on soybeans production. For the squared terms, farm size squared, agrochemical squared, and labour squared were found to have significant effects on soybean output in a long term. The negative coefficient (-0.176) for farm size squared is statistically significant at the 1% level. This means that continuing to farm soybeans on the same amount of land will result in a 17.6 percent reduction in soybean output.

Similarly, the coefficient of -0.197 for labour squared measured in man-days is significant at the 1% level for the pooled data. Also, the coefficient for the same variable (labour squared) for NCF is -0.412. This suggests that if same amount of labour is continuously employed in the production of soybean, with time soybean output will decrease by 19.7% for the pooled and 41% for NCF. These findings confirm that production function is a quadratic function and conform to production theory. These results are in harmony with Osman et al. (2018). Unit cost of agrochemicals, on the other hand, had a positive coefficient (0.374) and was statistically significant at the 1% level. This means that continuous application of the proper amount of pesticide herbicides in the study area enhances soybean output by 37.4 percent.

The significant interactive terms show whether conventional inputs in soybean production are substitutes or complements. The interaction of farm size and agrochemicals had an inverse relationship with soybean output. It was statistically significant at the 1% level and had a negative coefficient (-0.283). This means that having a larger farm and using agrochemicals on a regular basis does not always imply higher outputs. It also implies that farm size and agrochemicals are interchangeable, implying that you can expand your farm without using agrochemicals while still recording some outputs. This is in direct opposition to the study's presumption.

The interaction between farm size and labour had positive coefficient (0.467) and highly significant at 1%. The elasticity from Table 3 implies that as farmers increased their farm size and labour by a unit each, the output will increase by 47%. Donkoh, Ayambila, and Abdulai (2013) reached the same conclusion. This finding also corroborates those of Rahman and Barmon (2015), and Rahman et al. (2009). This finding indicates that farm size and labour are complements in soybean production. Labour in production process plays a critical role. Without labour, every activity in the production process will come to a halt. Labour helps in translating farm inputs to output (i.e. production goal). Hence, it is not surprising to have the interaction of farm size and labour having a positive coefficient. This also conforms to production theory.

The final interaction variable is agrochemicals and labour, which has a negative coefficient (-0.368), which is significant at the 1% level. This explains that the pairs of these input variables are substitutes in soybeans production. From the results, the return to scale value for the pooled is 0.806 showing decreasing returns to scale. It is 1.983 for CF and 0.103 for NCF. This shows increasing and decreasing returns to scale respectively for CF and NCF. The total of all the output elasticities in the first order term is the return to scale value. This means that increasing the usage of traditional variable inputs in the production process, such as farm size, seed, agrochemicals, and labor, will result in a less than proportionate rise in soybean output for the pooled and NCF. However, for CF increasing the usage of traditional variable inputs in the production process will lead to a more than proportionate increase in soybean output. This also means that if all other parameters remain constant, a 100 percent increase in all factors of production will result in an 81 percent increase in soybean yield for both CF and NCF. This result agrees with Mukhtar et al., (2018) who reported decreasing returns to scale, but differs from the findings of Abdulai et al. (2017), Waluse (2012), and Osman et al. (2018).

3.3 Drivers of Production Cost of Soybeans

The findings of the translog stochastic cost frontier model as shown on Table 4 for contract, non-contract and pooled data showed that, except for labour cost, the analysis included four input and one output factors, all of which had a positive effect on soybean production costs and were statistically significant. All the estimated coefficients for input prices were significant and had both positive and negative signs, indicating that the cost function behaved well.

Decision to participate in CF is a self-choice; hence there could be selectivity bias problem. Therefore, LIMDEP statistical software was used to perform the estimates to check whether there is evidence of selectivity bias in participating in CF in the study area. After the study, the rho value (see Table 4) was not significant, indicating that the data had no evidence of selectivity bias. As a result, the discussions are based on conventional SPF results.

Because all the input variable prices were mean-corrected, the estimates of the translog cost function show a relative change in soybean production costs resulting from a change in the explanatory variables (i.e., input prices). The discussion of the parameter estimates is based on the cost elasticities with respect to each individual input price evaluated at their mean values (Onumah et al., 2010). Column 1 (pooled results) represent the determinants of cost of soybean production.

The coefficient of unit cost of land was 0.162, which is marginally significant at the 10% level. The positive coefficient suggests that, in the research area, as the value of land increases by 100%, cost of soybean production will increase by 16.2 percent for all soybean farmers, holding other factors constant. This conclusion is supported by Jiang and Sharp (2014) and Abdulai et al. (2017).

The coefficient of the unit cost of seed was found to have positive coefficient (0.565) associated with cost of soybean production and it is significant at 1% level. As seed cost increases by 100%, cost of soybean production will increase by 56.5% for all soybean farmers, holding other factors constant. Seeds are one of the major farm inputs in production process. This finding is in line with the findings of Abdulai et al. (2017), who found that the cost of seeds can lead to an increase in total cost of production in Ghana. Masuku et al. (2014) in Swaziland came to similar conclusions. Farmers have been encouraged to adopt improved/certified seeds in production to reap benefits such as drought and pest tolerance. However, these seeds are mostly costly compared to the conventional seeds used for production. Adoption of improved seeds results in a higher cost of production.

A positive relationship (0.863) was found between the cost of agrochemicals and the cost of producing soybeans, which is statistically significant at the 1% level. When all other factors remain constant, a 100 percent increase in the cost of agrochemicals will result in an 86.3 percent increase in the cost of soybean production. In Ghana, Abdulai et al. (2017) found something similar.

As expected, the output of soybean in kilogram had positive association with cost of production. The output coefficient is 0.156, and it is statistically significant at 1%. In other words, if soybean output is increased by 100%, the total cost of soybean production will increase by 15.6 percent. This finding corroborates the findings of two Ghanaian studies, Abdulai et al. (2017) and Osman et al. (2018). In the production process, if the output (productivity) is higher, it increases cost of production.

Sixty percent (60%) of the squared and interaction terms had statistically significant effects on total production cost, indicating that the translog cost functional form is appropriate. The total cost of production increased or decreased for all second order terms; the coefficients of the squared terms for farm size, labour cost, seed cost, agrochemicals cost, and output. The squared terms explain the long-term effects of input prices on total cost of production. For instance, in future, 100% increase in labour cost and output would increase and decrease total cost of production by 5.9% and 10.8% respectively, *ceteris paribus*.

Table 4. Maximum Likelihood Estimates for the Parameters of the Stochastic Cost Frontier Model

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**6)**
Model	**Conventional SPF**			**Sample selection SFA**		
Variable	Pooled	CF	Non-CF	Pooled	CF	Non-CF
	Coeff. (Std. Err.)	Coeff. (Std.Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
Constant	0.072 (20.364)	0.076 (37.972)	0.077 (0.144)	0.750*** (0.083)	0.873*** (0.138)	0.640 (0.524)
Farm size	0.16166* (0.086)	0.342*** (0.124)	-0.224* (0.135)	0.337*** (0.090)	0.513*** (0.140)	-0.144 (0.290)
Labour	-0.081 (0.076)	-0.103 (0.1087)	-0.117 (0.132)	0.025 (0.066)	0.238** (0.107)	0.086 (0.39)
Seed	0.565*** (0.099)	1.531*** (0.202)	1.020*** (0.150)	0.482*** (0.129)	0.096 (0.144)	0.966** (0.471)
Herbicides	0.863*** (0.164)	0.845*** (0.210)	2.761*** (0.640)	0.820*** (0.160)	0.681** (0.313)	2.714 (2.909)
Output	0.156*** (0.053)	0.012 (0.082)	0.256*** (0.090)	0.055 (0.057)	0.042 (0.088)	0.288 (0.380)
Farm size sq.	0.192* (0.104)	0.064 (0.139)	0.265 (0.290)	0.141 (0.106)	-0.034 (0.152)	0.155 (0.412)
Labour sq.	-0.109** (0.049)	-0.070 (0.075)	-0.109 (0.072)	-0.028 (0.047)	-0.004 (0.097)	-0.092 (0.183)
Seed sq.	0.936*** (0.235)	0.337 (0.400)	2.280*** (0.361)	0.744*** (0.239)	0.378 (0.489)	2.074*** (0.501)
Herbicides sq.	-0.609*** (0.132)	-0.619*** (0.154)	-3.073*** (0.654)	-0.597*** (0.178)	-0.441 (0.373)	-3.009 (3.307)
Output sq.	-0.102*** (0.026)	-0.055 (0.036)	-0.181*** (0.039)	-0.070** (0.029)	-0.057 (0.038)	-.158** (0.074)
Farm size*labour	-0.035 (0.147)	-0.066 (0.189)	-0.174 (0.340)	-0.185 (0.129)	-0.127 (0.218)	-0.181 (0.741)
Farm size*Seed	-0.702*** (0.228)	-0.008 (0.338)	-2.020*** (0.350)	-0.714*** (0.244)	0.086 (0.441)	-1.878*** (0.574)
Farm size*herbicides	0.837*** (0.223)	0.703*** (0.256)	1.678*** (0.644)	0.839*** (0.220)	0.857 (0.602)	(1.628) 1.463)
Farm size*Output	-0.084 (0.056)	0.009 (0.086)	-.240*** (0.089)	-0.027 (0.061)	0.096 (0.107)	-0.220 (0.136)
Labour *Seed	-0.010 (0.164)	-0.175 (0.264)	0.619** (0.256)	0.058 (0.154)	0.237 (0.320)	0.557* (0.301)
Labour*Herbicides	0.186 (0.140)	0.355** (0.171)	-0.453 (0.492)	0.143 (0.171)	0.112 (0.378)	-0.452 (2.767)
Labour*Output	0.252*** (0.063)	0.254** (0.101)	0.240*** (0.082)	0.312*** (0.078)	0.289** (0.119)	0.261** (0.105)
Seed*Herbicides	-0.548*** (0.185)	-0.299 (0.257)	-0.705* (0.398)	-0.515** (0.219)	-0.438 (0.407)	-0.668 (2.952)
Seed*Output	-0.120 (0.111)	-0.213 (0.174)	-0.300 (0.184)	-0.099 (0.158)	-0.032 (0.171)	-0.245 (0.314)
Herbicide*Output	0.124 (0.094)	0.090 (0.109)	0.073 (0.443)	0.020 (0.120)	-0.026 (0.373)	0.118 (2.648)

Lambda	0.651 (42.345)	0.346 (74.44)	0.715*** (0.189)			
Sigma	0.603*** (0.0014)	0.639*** (0.003)	0.534*** (0.003)			
Sigma(u)				0.903*** (0.047)	0.965*** (0.051)	0.388* (0.233)
Sigma(v)				0.264***(0 .035)	0.172*** (0.041)	0.416*** (0.070)
Rho(w,v)				0.305 (0.635)	0.355 (1.657)	-0.044 (0.828)

Source: Field survey, 2019
Note: ***, ** and * represent 1%, 5% and 10% level of significance, respectively

The interaction terms show whether the variables are complements or substitutes in cost of production. If the two interaction variables have positive coefficient, it means that the variables are complements while negative means the variables are substitutes. Variables that have negative coefficients and statistically significant effects on total cost of production include farm size and seed cost and seed and agrochemicals. On the other hand, the interaction terms for farm size and agrochemicals as well as and labour cost and output cost were found to have positive coefficients.

Columns 2 and 3 of Table 4 present the determinants of costs of production by contract and non-contract soybean farmers. The first order variables used for the analysis all had positive coefficients but only farm size, soybean seed and agrochemical significantly exerted some effects on cost of soybean production.

The study found that farm size allocated for soybean production under CF has a positive coefficient of 0.342, which is highly significant at the 1% level. This means that, if all other factors remain constant, increasing farm size for soybean production by 100% in the case of contract farmers will result in a 34.2 percent increase in total production costs. The positive coefficient of farm size could also mean that contract farmers are more efficient in soybean production. Ideally, farmers who are into CF have access to farm inputs and this makes them to expand their farm sizes to enjoy economies of scale.

On the part of non-contract farmers, farm size was found to have inverse relationship to total cost of production of soybean. It had a -0.224 coefficient and was marginally significant at the 10% level. This means that if farm size is increased by 100%, the total cost of soybean production will be reduced by approximately 22.4 percent. This finding does not meet our *a priori* expectation, it is inconsistent with the findings of Saigenji (2011) who found a direct relationship between farm size and total cost of tea production in Vietnam.

In the study area, the price of soybean seed had a positive and statistically significant effect (coefficient=1.531) on total cost of production for contract farmers. This means that if the unit price of soybean seed for planting increases by 100%, the total cost of soybean production will rise by 153.1 percent, assuming all other variables remain constant. Access to soybean seeds, particularly improved/certified seeds is a key factor to participation in CF and productivity. As farmers have access to certified seeds, productivity is assured to increase thereby improving the welfare of smallholder farmers in the rural areas.

For non-contract farmers, both soybean seeds and agrochemical usage were found to have positive coefficients of 1.020 and 2.761 respectively and both are highly significant at 1% levels. The indication is that increasing the use of seeds and agrochemicals by 100% will result in a 102 percent and 276 percent increase in the total cost of soybean production, respectively. However, at the 1% level, output was found to have a positive coefficient of 0.256 and a statistically significant effect on total cost of production of non-contract farmers. This means that if non-contract farmers increase their output of soybeans by 100%, the total cost of production will increase by almost about 26%. This finding is consistent with the findings of Osman et al., (2018).

Only herbicide squared variable was found to have a significant impact on total cost of soybean production in the second order of variables for the pooled, CF and NCF. The herbicide squared has a coefficient of -0.609 for pooled, -0.619 for CF and -3.073 for NCF. The explanation to this effect is that the continuous use of herbicides on the same land will reduce total cost of production of the crop by about 61% for the pooled, 62% for CF and 307% for NCF.

Reducing the use of herbicide lowers the total cost of production. The health of consumers is also not threatened by these inorganic chemicals. Similarly, agrochemical usage and output square terms both have a negative relationship with the total cost of non-CF soybean production in the study area. Also, the output for contract farmers had a coefficient of -0.181, which is significant at the 1% level on the total cost of soybean production for non-contract farmers.

The interaction terms of the variables (third order term) found to have a positive effect on the total cost of production for contract farmers were farm size and agrochemicals; labour and agrochemicals; and labor and soybean output. These interaction term variables are all statistically significant and have positive coefficients, meaning that they are complements in usage to reduce total cost of soybean production.

Similarly for non-contract farmers the interaction terms of farm size and agrochemicals; labour and seed; and labour and output all have positive coefficients and statistically significant effects on non-contract farmers total cost of soybean production in the area. This means that the variables are complements in soybean production to reduce total cost of production by non-contract farmers. Additionally, farm size and seed; farm size and output; and seed and agrochemicals were found to exert negative coefficients effects on total cost of soybean production. They were all significant.

3.4 Determinants of Technical Efficiency, Allocative Efficiency and Economic Efficiency in Soybean Production

Examining the determinants of TE, AE, and EE in soybean production was one of the study's objectives. The traditional two-staged approach involves regressing efficiency estimate on proposed socioeconomic and environmental factors (Liu et al., 2016). The applications started with the standard linear models like ordinary, generalized and truncated least-squared models. These were followed by the Tobit, ordered logit and probit models, and then fractional response models (FRMs) (Gelan & Muriithi, 2012).

The Tobit regression was widely used and accepted until Simar and Wilson (2007) argued that censoring efficiency estimates between zero and one is questionable, especially given that efficiency estimates are not generated through a censoring process which could lead to inconsistent estimates. To address the problem of inconsistent estimates associated with OLS and Tobit approaches, Ramalho, Ramalho, and Henriques (2010) proposed FRMs in the second-stage analyses of the determinants of efficiency scores. Contrary to the OLS and Tobit models, the FRM deals with dependent variables defined on the unit interval, irrespective of whether or not the boundary value (0,1) is observed (Papke and Wooldridge, 1996; Ramalho, Ramalho, and Henriques, 2010).

The application of fractional regression got grounded with the work of Ramalho et al. (2010a). They criticized the work of Hoff (2007) and McDonald (2009) as inadequate because they used only logit specification to the neglect of alternative specifications such loglog and cloglog. The technical and allocative efficiencies were estimated using the stochastic frontier two-step estimation method. The two-stage technique is limited by the violations of the identical distribution of the u_i when the technical inefficiency effects are regressed on some unique farm features. The EE was computed using fractional regression. Table 5 displays the estimated EE, TE, and AE efficiency for the sampled farms. In connection to EE, if a variable's coefficient is positive, it shows that the variable has a positive association with efficiency and vice versa. Similarly, positive coefficients for variables under the TE and AE indicate that the variable has a positive effect on efficiency and vice versa.

Table 5: Maximum likelihood Estimates for Parameters of the Fractional Regression Model

Variable	TE		AE		EE	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Gender	-0.048	0.092	-0.086	0.075	-0.014	0.033
Education	0.168**	0.091	0.158**	0.078	0.036	0.032
Farm size	-0.046	0.034	-0.001	0.011	-0.025	0.001
Age	-0.000	0.003	-0.001	0.002	0.008	0.009
Experience	0.003**	0.017	0.004	0.015	0.001*	0.007
Crop diversity	0.010	0.046	-0.013	0.038	-0.047***	0.015
Off farm activity	-0.522***	0.112	-0.478***	0.098	-0.102***	0.039
Extension	0.229**	0.132	0.206**	0.113	0.039**	0.044
Credit	0.253	0.083	-0.055	0.069	0.035	0.026
Training	0.918**	0.111	0.229	0.087	0.229**	0.113
Credit_resid	-0.138	0.114	-0.107	0.097	0.052	0.050
CF	0.039**	0.085	.049**	0.070	0.041**	0.029
_cons	0.269*	0.222	0.004***	0.189	0.069**	0.147
Number of obs.	374		374		374	
Wald chi2(10)	52.23		56.36		27.25	
Prob > chi2	0.0000		0.0000		0.0071	
Pseudo R2	0.0334		0.0254		0.0025	
Log pseudo likelihood	-242.714		-252.615		-164.825	

Source: Field survey, 2019;
Note: ***, ** and * represent 1%, 5% and 10% level of significance, respectively

The variable, credit was suspected to be endogenous since cash credit might be invested in soybean production which could make the farmer more efficient (income effect). In the same vein, a farmer may be efficient because of his/her access to credit. The potential endogeneity of the variable (credit) was addressed utilizing the control function approach proposed by Wooldridge (2015).

The approach requires the specification of the prospective endogenous variable (i.e., credit) as a function of explanatory variables impacting access to credit, combined with a set of instruments in a first-stage probit regression. Instead of using the predicted values of credit variable as in two stage-least-squares, the observed values of credit variable and the generalized residual (Credit_res) from a first-stage regression are used as covariates in the SPF model. Including the residual serves as a control function, enabling the consistent estimation of the credit variable. The residual term, credit_resid is not significant in the determination of efficiency of soybean farmers indicating the exogeneity of this variable (Wooldridge, 2015). The results of the endogeneity test are shown in the appendix.

To begin, education had no significant effect on EE, but it did have significant positive effects on both TE and AE at the 5% level in the study. This means that as a farmer's formal education years increase, so does his or her allocative and TE. Amaza and Olayemi (2000) found a positive relationship between education and TE and AE, and this finding is consistent with their findings. A farmer's knowledge, skill, and attitude improve as his or her years of schooling increase, and he or she is more likely to adopt new technologies and best practices, according to Ogundari and Ojo (2006). Similarly, educated farmers can obtain relevant information from a variety of sources and make better informed decisions than their less educated colleagues to improve farm management and, as a result, increase soybean production efficiency (Mengistu, 2014). This finding is compatible with Mukhtar et al., (2018) research in Pakistan's Peshawar District, although it contradicts Chirwa's findings (2007).

In the efficiency model, farmers who have been producing soybeans for a long time have been found to be more technically and economically efficient, as indicated by the positive sign of experience and statistical significance at 5 percent and 10%, respectively. In addition, farmers with several years of experience may be more technically and economically efficient than farmers with only a few years of experience. This finding is consistent with the findings of Donkoh et al. (2013), who reported that experience was essential in determining the efficiency of tomato farmers in the Tono irrigation schemes in the Upper East region of Ghana. Okike et al. (2004) went on to say that, in this situation, soybean farming experience is a crucial element contributing to TE because of the expected acquisition of dexterity with time. Lapple (2010) also argued that an increase in agricultural experience offers greater awareness of the production context in which choices are made. On the other hand, Oyewo et al., (2009) found maize farmers with several years of experience to be less technically efficient in Nigeria's Ogbomoso South local government area.

Crop diversification had negative effect on EE and significant at 1%. This means that cultivation of many food crops decreases farmers' EE. This also means that, as more farmers cultivate many crops, their AE also decreases. Cultivation of several crops by farmers makes them incur more cost and make them have difficulty in allocating farm inputs and other resource to maximize output.

Off-farm activity had negative and significant effect at 1% for AE, EE and AE. This means that farmers who earned income in other ways than farming were inefficient economically, technically, and allocatively. The reason for this may be that time and other resources invested into farming activities by these farmers are less compared to investment in the other things they do.

Access to extension services was found to have a favorable and significant impact on technical, allocative and cost efficiencies. The goal of Extension is to improve farmers' knowledge of agronomic methods like pest and disease control, adoption of improved seed varieties, soil and water conservation technologies, and how to properly allocate resources to minimize waste. This puts the framer in a better position to make the most of his or her limited resources in order to accomplish better results and so improve efficiency.

The coefficient of the training variable was positive and statistically significant at 5% for both TE and EE but not AE. This was in line with *a priori* expectations. This means that farmers who had access to training on soybean production were more economically, technically and allocatively efficient than those who had no training. This finding is expected because access to training exposes farmers to new technologies, better agronomic practices and information sharing and dissemination, all these can help a farmer in better managing his/her farm to be efficient.

Soybean CF had a positive coefficient and was statistically significant at 5% across EE, TE, and AE. This indicates that farmers who were into soybean CF were not only economically efficient but also technically and allocatively efficient in soybean production, which is in line with the study's *a priori* expectation. The reasons for this finding are not far-fetched; 1)

Soybean contract farmers had access to regular trainings from contracting firms who teach them how to better manage their farms, 2) they were also provided with inputs such as herbicides, weedicides, tractor services and cash credit at lower costs making them allocatively efficient 3) contract farmers were also taught how to effectively allocate their inputs and resources to avoid waste thereby reducing cost. This makes them economically efficient.

3.5 Comparison of Efficiency Distribution Technical Efficiency, Allocative Efficiency, and Economic Efficiency for Contract Farmers

Table 6 contains information on technical, allocative, economic, and scale efficiency. The efficiency range revealed a significant disparity between the lowest and highest efficiency indices. Contract farmers had an average TE score of 0.92, with minimum and maximum values of 0.179 and 1.00 respectively, implying that 8% [100-92] of the production is lost due to technical inefficiency alone. This implies that the average farmer producing under contract could increase their production of soybean by improving their technical efficiency.

Similarly, the mean allocative efficiency level among contract soybean farmers in northern region of Ghana is estimated to be 86.9%, with minimum and maximum values of 0.612 and 1.00 respectively. The mean allocative efficiency level is higher compared to that of Ajao, Ogunniyi, & Adepoju (2012); Akhilomen, Bivan, Rahman, & Sanni (2015); The allocative efficiency estimates suggest that an average soybean farmer would enjoy a cost saving of 13.1% derived from [1 – (0.869/1.00) x 100] if he/she were to attain the level of the most efficient farmer. The most allocatively inefficient farmer would have an efficiency gain of 38.8% derived from [1-(0.612/1.00) x 100] to attain the level of the most efficient farmer. This indicates that there is a great opportunity to increase the efficiency of soybean producers by the reallocation of resources in cost minimizing way.

Table 6. Efficiency Scores Distribution TE, AE and EE for Contract Farmers

	Contract farmers						Non-contract farmers					
	TE		AE		EE		TE		AE		EE	
Efficiency range	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
0.00-0.29	6	2.97	0	0	0	0.00	2	1.16	7	4.07	1	0.58
0.30-0.39	3	1.49	0	0	1	0.50	1	0.58	7	4.07	0	0.00
0.40-0.49	0	0.00	0	0	0	0.00	0	0	17	9.88	0	0.00
0.50-0.59	5	2.48	0	0	0	0.00	2	1.16	32	18.60	0	0.00
0.60-0.69	8	3.96	2	0.99	6	2.97	3	1.74	29	15.70	3	1.74
0.70-0.79	5	3.47	45	24.26	12	5.94	0	0.00	5	2.91	5	2.91
0.80-0.89	4	1.98	78	38.61	30	15.84	1	0.58	0	0.00	16	8.14
0.90-1.00	169	83.66	73	36.14	151	74.75	165	94.77	77	44.77	149	86.63
Total	200	100.00	200	100.00	200	100.00	174	100.00	174	100.00	174	100.00
Mean	0.920		0.869		0.943		0.973		0.734		0.866	
Min.	0.179		0.612		0.348		0.170		0.079		0.031	
Max.	1.00		1.00		0.999		1.00		0.999		0.999	

Source: Field survey, 2019

The economic efficiency of an average soybean farm was estimated as 0.943 for CF meaning that an average soybean farmer producing under contract in the study area experiences economic efficiency that is 6% below the frontier. A good number of them almost 75% is operating at an EE above 90%. The result of the average economic efficiency is high compared to Magreta, Edriss, Mepemba, & Zingore (2013), Degefa (2020) and Shalma (2014) who had 53.32%, 54% and 64.7% respectively. Again, Akhilomen, Bivan, Rahman, & Sanni (2015) who analyzed economic efficiency of pineaple production had a mean economic efficieincy of 64.3%.

Furthermore, the results show that a farmer with an average level of EE would save roughly 93.39 percent (i.e., 1- (0.943/0.999) x100) in order to reach the most efficient level. Similarly, to reach the level of the most efficient farm, the most economically inefficient farm would need to gain 33.83 percent from (1- (0.348/0.999) x100).

3.6 Efficiency Distribution TE, AE and EE for Non-Contract Farmers

Table 6 also shows the efficiency scores for non-contract farmers in the study. The results show that the minimum and maximum TE values are 0.173 and 1.00, with a mean of 0.973. This implies only 2.7% [100-97.3] of the production by NCF is lost due to technical inefficiency. The production losses incurred by NCF due to TE are better than their CF counterparts. NCF may be managing their resources better to avoid waste due to the fact they do not have access to the benefits that comes with contracting hence cannot afford to waste their meager resources hence the reason they are better off technically.

Furthermore, the mean allocative efficiency level among non-contract soybean farmers in northern region of Ghana is estimated to be 73.4%, with minimum and maximum values of 0.079 and 0.999 respectively. The mean allocative efficiency level is higher compared to that of Ajao, Ogunniyi, & Adepoju (2012); Akhilomen, Bivan, Rahman, & Sanni (2015); Magreta, Edriss, Mepemba, & Zingore (2013); Degefa (2014). The allocative efficiency estimates suggest that an average non-contract soybean farmer would enjoy a cost saving of 26.5% derived from [1 – (0.734/0.999) x 100] if he/she were to attain the level of the most efficient farmer.

In terms of EE distribution, about 86.63% of the non-contract farmers' EE is between the range of 0.90-1.00 and 8.14% is between 0.80-0.89. With EE distribution being skewed to the efficiency range above 0.80. The mean EE of 0.866 of non-contract farmers means that, in the study area NCF experiences EE that is 13.4% below the frontier. The result of the average EE is higher compared to Magreta, Edriss, Mepemba, & Zingore (2013), Degefa (2014) and Shalma (2014) who had 53.32%, 54% and 64.7% respectively. Again, Akhilomen, Bivan, Rahman, & Sanni (2015) who analyzed economic efficiency of pineaple production had a mean economic efficieincy of 64.3%.

Furthermore, the result also indicates that a NCF farmer with average level of economic efficiency would enjoy a cost saving of about 13.31% (i.e., 1- (0.866/0.999) x100) to attain the level of the most efficient household. Also, the most economically inefficient household would have an efficiency gain of 96.9% derived from (1- (0.031/0.999) x100) to attain the level of the most efficient household. This implies that smallholder non contract soybean farmers' productivity could increase if key factors that currently constrain overall efficiency are addressed adequately.

4. Conclusions and Recommendations

The study findings reveal that contract farming had a positive and significant effect on the technical, allocative, and economic efficiency of soybean production. Farmers participating in contract farming arrangements were more efficient compared to their non-contract counterparts. Factors such as education, farming experience, access to extension services, and training positively influenced the technical, allocative, and economic efficiency of soybean production. However, off-farm activities and crop diversification had a negative impact on the allocative and economic efficiency of soybean production.

There was a significant disparity between the lowest and highest efficiency indices among both contract and non-contract farmers, suggesting the potential for improvement. The mean technical efficiency score for contract farmers indicated an 8% loss in production due to technical inefficiency, while the mean allocative efficiency score suggested a potential cost saving of 13.1%. The mean economic efficiency score for contract farmers meant an average farmer experienced economic efficiency that was 6% below the frontier. Interestingly, non-contract farmers had a higher mean technical efficiency score compared to contract farmers, but lower mean allocative efficiency and economic efficiency scores.

Based on the findings, it is recommended to promote and expand contract farming arrangements for soybean production, as it has been shown to enhance the technical, allocative, and economic efficiency of farmers. Investing in education and training programs for farmers to improve their knowledge and skills in efficient resource allocation and adoption of best agricultural practices is crucial. Strengthening and improving access to extension services is also recommended, as they play a crucial role in enhancing farmers' efficiency. Encouraging farmers to focus on specialized crop production rather than diversifying into multiple crops is advisable, as crop diversification negatively affects allocative and economic efficiency.

Additionally, investigating and addressing the factors contributing to the significant disparities in efficiency indices among farmers is essential to bridge the gap between the most and least efficient producers. Implementing policies and interventions aimed at improving resource allocation and cost minimization strategies, particularly for non-contract farmers, is recommended to enhance their allocative and economic efficiency. Finally, conducting further research to identify and address the specific constraints faced by non-contract farmers, which may be hindering their allocative and economic efficiency, is vital.

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