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AGGLOMERATION EXTERNALITIES, PRODUCTIVITY AND TECHNICAL EFFICIENCY OF SOYBEAN FARMS IN GHANA

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Agglomeration, Agriculture, Efficiency, Externalities, Farmer Associations (FA), Farm Density (FD), Soybean, Stochastic Frontier.

ABSTRACT

The study set out to identify agglomeration externalities in Ghana's soybean sector, assess soybean output elasticities with respect to input-use, analyze the technical efficiency levels and determine the effect of agglomeration externalities on the productivity and technical efficiency of soybean farms. The paper identifies some components of agglomeration externalities across the soybean sector and defines agglomeration externalities by two indexes; industry size, captured by whether the farmers belong to Farmer Associations (FA) and if they do, what their Farm Densities (FD) are - measured by the number of smallholder farms per square kilometre that the individual farms belong to. A stochastic frontier model, with the agglomeration indexes FA and FD, and a technical efficiency model are specified to ascertain the effects of agglomeration externalities on the production frontier and efficiency of soybean farms. The estimation of the frontier model is carried out on data collected from 393 soybean farms in the Upper East and Upper West Regions of Ghana. Hypotheses tests carried out using Log-likelihood ratio estimates indicate that the translog stochastic production model is the best fit for the data. The results show that, for the production frontier, FA and FD (with coefficients 1.02 and 0.03 respectively) have a significantly positive relationship with productivity. The positive relationship between productivity and farm density suggests the presence of positive congestion externalities. FD has a positive influence on efficiency but FA was found to have a negative relationship with the technical efficiency of soybean farms. The results of the Maximum-Likelihood Estimates of the stochastic frontier model show that a percentage increase in seed, capital, labour and fertilizer, respectively, will increase the soybean production frontier by 0.14, 0.14, 0.28 and 0.41 percent. The soybean sector exhibits diminishing returns to scale (0.98 percent increase in output with one percent increase in all input) with the mean technical efficiency index of the sector estimated at 0.52. Age and gender have a negative relationship with efficiency, indicating that younger farmers are more efficient than their older counterparts and female farmers are more efficient than the males. Increase in frequency of farmer-extension agent interactions also leads to increase in the efficiency of the farmers. The findings of the study confirm that FA and FD have significant influence on productivity and technical efficiency of soybean farms. The implications of these results are that there is the need for government(s) and stakeholders to help improve productivity and efficiency in the soybean sector by helping farmers to better access positive agglomeration externalities.

BACKGROUND

Soybean has over the years become an important source of foreign exchange for Ghana, with exports being mostly to the United Kingdom. In recent times, the local industry in Ghana has become one of the main focuses of soybean production, soybean being considered considerably as a nutritional supplement and also as playing a significant role in ensuring food security especially for farmer households. About 150,000 MT of soybean is demanded in Ghana every year, with the largest proportion of this quantity going into soybean oil and meal production. The advantages of soybean over other leguminous crops include comparatively low susceptibility to pest and disease attacks and the ability to store the grains easily, making it easily cultivable by smallholder farmers with very limited resources.

Technical efficiency and productivity studies abound in agriculture to enable the assessment of the effectiveness and efficiency of input-use and also measure production and efficiency levels against an optimum production frontier of 1 (100%). Through development projects in Ghana, such as the Agricultural Value Chain Mentorship Project (AVCMP), the Council for Scientific and Industrial Research (CSIR) has extended some soybean technologies to the Northern parts of Ghana to help improve the efficiency and productivity of the sector. These technologies include and/or are embodied in GAPs, use of certified seeds, Integrated Soil Fertility Management (ISFM), Integrated Pest Management (IPM), amongst others. In spite of these technology interventions however, in 2011, Ghana's Ministry of Food and Agriculture (MoFA) reported that the average soybean yields of farmers was about 1.5 MT/Ha, which is 35 percent below predicted achievable yields of 2.3 MT/Ha (MoFA, 2011).

Efficiency studies provide the avenue to explore and proffer recommendations to improve efficient and effective utilization of available input resources to improve productivity. These studies are necessary as they address the effectiveness of input combinations in order to produce optimum output levels without necessarily increasing the levels of input used for the same quantum of economic activity. Some studies have been carried out on efficiency and productivity for some common staple crops in Ghana. There however seems to be very scanty information pertaining to the efficiency and productivity of soybean farming (Mohammed *et al.,* 2016). Studies on technical efficiency and productivity encompass the maxim of producing more with less. This is particularly important for a developing society like Ghana that has comparatively less resources and high poverty ratings among its farmers. There is also the issue of lack of resources, especially for improved technology, leading to low productivity in the soybean sector (Etwire *et al.,* 2013). In the face of scarce input resources, farmers would want to maximize input-use to enhance productivity through efficiency. These studies are relevant to the sector as the estimations give indications as to the efficient utilization of available input factors to optimize production.

Empirical studies on agglomeration externalities have been conducted over the years to establish a link between the size of an industry and the externalities that arise among the firms that belong to these industries. In carrying out these studies, there has been put forward a hypothesis, according to Battese and Tveteras (2006), that there exists a positive relationship between the size of an industry (industry agglomeration) and the externalities that arise among firms belonging to the industry, and this positive relationship may lead to increase in productivity. These externalities could occur between competing firms, between a firm and its customers or even a firm and its vendors (Battese and Tveteras, 2006). This study provides information gleaned from results on empirical analysis conducted on a primary production sector for small-holder soybean farmers. This is with the view that the soybean sector can in so many ways be likened to and treated as an industry due to the advent of technology, labour specialization and indivisibilities that are associated with physical capital and labour (Puga, 2009).

The concept of agglomeration externalities embodies spillover information, among other factors, that may lead to knowledge pertaining to inputs that are used by farmers, distribution routes, processing methods, marketing strategies, and production methods. These externalities may arise from soybean farmers (especially small-holder farmers) forming and/or belonging to groups/associations (FA) and proximity of farms to each other. The externalities may also arise from Farm Density (FD), measured in this study as the number of farms per square kilometre. Increased levels of localized knowledge spillovers could lead to fewer errors in decision-making and this could lead to a more efficient and productive soybean farming system. These agglomerations may be necessitated by the uneven distribution of local endowments, either natural or man-made, such as institutions, infrastructure and the spatial relationship among economic structures (Maciente, 2013; Henderson et al., 2001). However very few technical efficiency studies consider agglomeration externalities, as is the case in Ghana.

The externalities that arise from agglomeration could be both positive and negative. Some of the negative externalities could be an increase in the incidence of pests or a spread of crop diseases among farms due to their close proximity to each other, or due to harmful information that is spread among farmers because they belong to the same associations. There are also, however, positive externalities that may arise from these groupings. Some of these are increased levels of localized knowledge that may lead to productivity gains and translate into higher returns that may in turn attract a lot more players and actors into the farming sector. This may lead to the production of further externalities in an autonomous and self-reinforcing cycle (Markusen, 1996; Rosenthal and Strange, 2001).

It would therefore be in the interest of researchers and stakeholders to be in the know about measurements pertaining to these parameters, to better harness available resources to ensure that the positive externalities are maximized as the negatives are minimized (Puga, 2009). Unfortunately, due to the absence of such studies, especially for the soybean sector in Ghana, this information is either absent or inadequate and as such we are unable to capitalize on the situation and harness it to our advantage.

Following the study conducted by Battese and Tveteras (2006), this study looked at a three-pronged approach to reaching its set-out objectives. First of all, measurements of agglomeration externalities were carried out on farm-level data rather than on aggregate industry data. Aggregation biases that are associated with internal returns to scale (IRS) and assumptions of cross-industry/cross-sector homogeneity for input variables included in the production frontier were avoided. By extension therefore, estimates of external returns to scale were only slightly influenced or not at all (Burnside, 1996). Secondly, there was a separation of analysis of effects on the production frontier and on technical efficiency and not estimates on average production functions. Thirdly, the study provides evidence for a primary production sector; the soybean farming sector.

THEORETICAL FRAMEWORK

The production frontier model was adopted for this study. Following Aigner et al. (1977), Meeusen and van den Broeck, (1977) and Battese and Corra, (1977), we define an error term that consists of an exogenous term (v), made up of factors that the farmer cannot control, and an endogenous term (u) that consists of factors that the farmer is able to control. The u is non-negative, random, independently distributed, and accounts for technical efficiency in production. u and v are independent random variables. The stochastic frontier model is expressed as:

$$y = f(x_i, \beta)e^{v-u} \tag{1.1}$$

where *y* represents the output (Kg/Ha) scaled down by land size, from output per acre to per hectare so as to avoid dealing with huge land size figures. *f (.)* represents the production frontier function, *u* is the endogenous term, which is a random variable that is non-negative and is associated with efficiency of production. *v* represents the exogenous, traditional random error term. If $u > 0$ there is inefficiency and therefore production falls short of the frontier. If $u = 0$, then the production lies on the frontier and so is therefore efficient (Mohammed et al., 2016). The stochastic frontier model is a translog function given as:

$$ln\, y_i = \beta_0 + \sum_r \beta_r \;+ \sum_k \beta_k \,ln\, x_{ki} + \sum_j \sum_{k \geq j} \beta_{jk} \,ln\, x_{ji} \,ln\, x_{ki} + (v_i - u_i) \tag{1.2}$$

$ln\, y_i$ represents the natural logarithm of the output of farm *i* (representing productivity), x_{ki} represents the input levels and the translog form, $ln\, x_{ki}$, implies that no a priori restrictions are imposed with respect to internal returns to scale (Batesse and Tveteras, 2006). The translog production function, which is flexible in nature, allows for farm-specific efficiency measurements and analysis of interactions among variables (Antle, 1984).

Equation 1.2 is further expanded into equation 1.3 to include agglomeration. The new form is:

$$ln\, y_i = \beta_0 + \sum_r \beta_r E_r + \sum_o \beta_o ln\, E_o + \sum_k \beta_k \,ln\, x_{ki} + \sum_j \sum_{k \geq j} \beta_{jk} \,ln\, x_{ji} \,ln\, x_{ki} + (v_i - u_i) \tag{1.3}$$

where E_r is agglomeration (captured by FA), E_o is agglomeration (captured by FD), U_i is technical efficiency and *x* represents the input variables. The study also follows Battese and Coelli (1995) as well as Onumah et al. (2010) and estimates the technical efficiencies using the technical efficiency model specified as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i;\beta)\cdot \exp(v_i - u_i)}{f(X_i;\beta)\cdot \exp(v_i)} = \exp(-u_i) \tag{1.4}$$

where v_i and u_i are the exogenous and endogenous parameters for farm *i*. Y_i is the output level for the *i*th observation and Y_i* is the maximum potential farm output level, considering that the inputs, *X*, are combined with maximum efficiency in a situation of 'best farm practice'. The difference between Y_i and Y_i* is embedded in the u_i. $Y_i = Y_i$* when $u_i = 0$ implying technical efficiency as a result of the production lying on the frontier (Onumah et al., 2010).

Thus, the technical efficiency of production for the *i*th firm is derived using the technical efficiency model as specified in equation 1.4. The model can also be specified as:

$$TE_i = \exp(-U_i) = \exp(Z_i\beta - W_i) \tag{1.5}$$

where for farm *i*, *Z* is a vector of all explanatory variables that are associated with the technical inefficiency effects and β is a vector of unknown parameters to be estimated. Thus, the parameters of both the inefficiency model and the frontier production function are concurrently estimated (Batesse and Coelli, 1995). Equation 1.5 can further be expanded to include FA and FD to estimate the effects of agglomeration on efficiency. One of the Z_is can represent FD and FA to determine the effect of agglomeration externalities on technical efficiency. The means, μ_i, associated with the technical efficiency effects are assumed to be a function of regional and farm characters and the functional form is specified as:

$$\mu_i = \delta_0 + \sum_{m=1}^{M} \delta_m Z_{mi} \tag{1.6}$$

Materials and Methods

The Study Area

The study was conducted in the Upper East and Upper West regions of northern Ghana. These regions were selected for their vibrancy in soybean farming and production. Data was collected from four communities within four districts from the two regions (Lawra in the Lawra district, Nyoli in the Wa West district, Gambrungu in the Bongo district and Konkomada in the Garu-Tempane district). The Lawra and Wa West districts are situated in the Upper West Region of Ghana, and Bongo and Garu-Tempane in the Upper East Region of Ghana. The Lawra district is situated in the north-western part of the Upper East Region, and is bordered to the north and to the east by the Nandom and Lambussie districts, respectively, and to the south-west and west, by Burkina Faso (GSS, 2013). The Wa West district is situated in the western part of the Upper West Region and shares borders with the Northern Region on the south, Nadowli district on the north-west, Wa on the east and Burkina Faso on the west.

The Bongo and Garu-Tempane districts are both located within the south-eastern part of the Upper East Region. The Bongo district shares boundaries with Burkina Faso, Kassena-Nankana East, Bolgatanga and Nabdam district to the north, west, south-west and south-east respectively, while the Garu-Tempane district shares boundaries with Bawku, Bunkpurugu-Yunyoo district, Bawku West district and Togo to the east.

Lawra and Wa West districts have a total land size area of about 527.32 and 1492 square kilometres respectively, while Bongo and Garu-Tempane districts have respective land size areas of about 495.5 and 1060.91 square kilometres (GSS, 2013).

The four districts lie within the Guinea and Sahel Savannah grassland zone which provide favourable and conducive ecological variables that make it conducive to grow cereal crops such as soybean, millet, maize, groundnuts, cowpea, among others.

Sampling

Data was collected from 400 farmers, 200 each from the Upper East and Upper West regions of Ghana. The sample size after data cleaning was 393 farmers; 196 from the Upper East and 197 from the Upper West Regions. Of the 393, 200 were farmers who belong to farmer groups or cooperatives (FA) and the remaining 193 did not (non-FA).

A multistage sampling method was employed in the selection of the study areas. The Upper East and Upper West regions were purposively selected for their vibrancy in soybean production, as they are located within the savannah belt where soybean thrives best in Ghana (MoFA, 2011). The districts within which the towns for the research were sampled from were also purposively selected, the decision and choice informed and influenced by MoFA, USAID and MEDA who have carried out extensive work on soybean in these areas; Lawra and Wa West districts from the Upper West Region, Bongo and Garu-Tempane districts from the Upper East Region.

Finally, the simple random sampling method was used to select the towns for the study. Through the lottery method, four communities from the districts were selected from a list of communities that are active soybean producers.

Questions pertaining to productivity, efficiency, socio-economic characteristics and other relevant aspects of the study were asked farmers through questionnaires. These well-structured questionnaires were issued to active soybean farmers as part of the survey and contained questions which tried to tease out relevant information concerning the soybean farmers and their farming activities. The aim was to elicit information relevant to the research.

Methods of Analysis

Empirical Model Specifications

Following Battese and Tveteras (2006), and Battese and Coelli (1995), the models for the analysis are specified with both a technical efficiency model and a stochastic frontier production model. Both the frontier production and efficiency models incorporate a parameter, *E*, which represents agglomeration externalities. For this study, the agglomeration externalities (*E)* by the two variables FA and FD. The technical efficiency model is specified in equation 1.4 and caters for the exogenous and endogenous factors v_i and u_i.

Identifying Agglomeration Externalities in the Soybean Sector

The identification of agglomeration externalities was done by eliciting information on the two parameters the study adopted for measuring agglomeration, that is E_{FAi}, which represents agglomeration externalities/effects arising from farmer associations, E_{FDi}, representing externalities of agglomeration arising from farm density in the areas of study. FA and FD are thus proxies representing agglomeration externalities in the efficiency and production frontier models. FA and FD were used as unconventional variables in the models to determine the effect that they have on both technical efficiency and productivity.

Farmers sampled for questioning were asked to indicate whether or not they belonged to any form of farmer association, cooperative or FBO. For farmers who belong to farmer associations, farm densities were assessed by ascertaining the number of soybean farms per every square kilometer within which the respective farm(s) is located. Farm Density was not considered relevant for farmers who operate independently. However, proximity to other soybean farms was assessed to establish the level of interaction and externalities, if any, that occurred and arose from proximity to each other.

The Frontier Model

The production function put forward by Caballero and Lyons (1990), which takes a log-linear Cobb-Douglas form, was used to assess the elasticities of the output in relation to inputs. The production function is specified as;

$$ln\ Y_i = \beta_0 + \sum_{FA}\beta_{FA}\, E_{FA} + \sum_{FD}\, \beta_{FD}\, ln\ E_{FD} + \sum_{n=1}^{n=4} \beta_k\, ln\ x_{ki} + \sum_j \sum_{k \geq j} \beta_{jk}\, ln\ x_{ji}\, ln\ x_{ki} + (v_i - u_i) \quad (1.7)$$

where Y_i is productivity (measured in kilograms per hectare), E_{FA} is agglomeration with respect to Farmer Association, E_{FD} is agglomeration with respect to Farm Density and u_i is technical efficiency. The study looked at the implications on productivity from the combination of four inputs (x), namely SEED (Seed) measured in kilograms, K (capital) measured in Ghana cedis (GHS), LAB (Labour) measured in person-days and FERT (fertilizer) which was captured as an intermediate input.

Productivity Assessment Variables

The variables measured to assess productivity, a description of these variables and parameters, their units of measurement and individual *a priori* expectations are presented in Table 1.1. For the input variables seed, capital, labour and fertilizer, it was expected that the relationship between them and productivity is positive, indicating an increase in Y (output) with increases in the quantity of input used.

The SEED variable represents the quantity in kilograms of soybean seeds planted by soybean farmers per season. K represents the capital that the farmer invested in his farming activities and is measured in Ghana cedis. LAB was measured by the average number of person-days spent on the farm per season. FERT was captured as an intermediate input and so was measured in Ghana cedis. It represents the monetary value of inoculant used per season for soybean farming.

Seed (Kg), capital (GHS), Labour (person-days) and fertilizer (Kg) were measured as continuous variables. FA was measured as a dummy variable. The studies expectation was that agglomeration externalities for the production model could either have positive or negative effects on productivity.

Table 1.1: Productivity variables, description, unit of measurement and a priori expectations

Variable	Description	Unit of measurement	*A priori* expectation
Y	OUTPUT	Kg	
Input Variables:			
SEED	Seed	Kg	+
K	Capital	GHS	+
LAB	Labour	Person-days	+
FERT	Fertilizer	Intermediate input (GHS)	+
Agglomeration:			
FD	Farm Density	Number of farms/sq. km	+/-
FA	Farmer Associations	Dummy: 1 = Yes 0 = No	+/-

Source: Survey, 2017

Inefficiency Model

The technical efficiencies were elicited and estimated. Here, the efficiency levels of the farms are compared to a frontier of 1 (100%) to determine farmers' levels of efficiency. There is technical inefficiency when production lies below the frontier (that is $u_i > 0$).

From the base model, the assumption governing the means u_i related to the technical efficiency effects is that they are a function of farm and industry characteristics. The technical efficiency effects are thus assumed to be defined by the inefficiency model specified as:

$$\mu_i = \delta_0 + \delta_{MS}\, MARSTAT_i + \delta_{EXP}\, EXP_i + \delta_{EXPSoy}\, EXPSoy_i + \delta_{AGE}\, AGE_i + \delta_{GEN}\, GEN_i + \delta_{EXTNum}\, EXTNum_i + \delta_{HHS} HHS_i + \delta_{EDUC}\, EDUCYrs_i + \delta_{FA}\, FA_{ri} + \delta_{FD}\, FD_{ri} \quad (1.8)$$

where $MARSTAT_i$ is the Marital Status of farmer, AGE_i is the age of farmer, HHS_i is the household size, EXP_i is experience in farming, GEN_i is gender of farmer, $EDUCYrs_i$ is the number of years of education of the farmer, $EXPSoy_i$ is farmer experience in soybean farming, and $EXTNum_i$ is number of visits to the farms by extension officers. The inefficiency model captures agglomeration externalities (FA and FD) to determine the effects of agglomeration on the efficiency of soybean farms.

Variables to Assess Technical Efficiency

For the efficiency variables, *a priori* expectations for farmer experience (EXP), soybean farming experience (EXPSoy), age of farmer (AGE), number of extension agent visits to soybean farms (EXTNum) and farmer's educational level (EDUCYrs) were expected to have a positive relationship with technical efficiency (Table 1.2).

Efficiency variables such as marital status of the farmer (MARSTAT) - measured as a dummy variable, gender of the farmer (GEN) and the household size of the farmer (HHS) were expected to either have a negative or positive relationship with efficiency depending on the economic dynamics present in the soybean sector.

Table 1.2: Productivity variables, description, unit of measurement and a priori expectations

Variable	Description	Unit of measurement	*A priori* expectation
Y	OUTPUT	Kg	
Inefficiency Variables:			
MARSTAT	Marital Status	Dummy: 1 = Yes 0 = No	+/-
EXP	Experience in farming	Years	+
EXPSoy	Experience in soybean farming	Years	+
AGE	Age	Years	+
GEN	Gender	Dummy: 1 = Male 0 = Female	+/-
EXTNum	Extension (number of visits)	Number	+
HHS	Household Size	Number	+/-
EDUCYrs	Education	Years	+
FD	Farm Density	Number of farms/sq. km	+/-
FA	Farmer Association	Dummy: 1 = Yes 0 = No	+/-

Source: Survey, 2017

EXP and EXPSoy are inefficiency variables capturing experience in farming and experience in soybean farming, respectively, measured in years. Age of the farmer, measured in years, was expected to have a positive relationship with efficiency. The EXTnum variable represents number of times that extension agents visit soybean farmers. This is a measure of the frequency (or intensity) of farmer interactions with extension agents. GEN represents the gender of the farmer and was captured as a dummy variable with 1 and 0 representing male and female respectively. A positive relationship between GEN and efficiency would indicate that males are more efficient and vice-versa. The study also considered household size (HHS) as a relevant explanatory variable in the inefficiency model. It was captured as the number of people (adults and children) that are in the household.
As is in the case of productivity estimation, the researchers expected that agglomeration externalities (captured by FA and FD) would significantly influence the efficiency of soybean farms.

Elasticities

The translog stochastic production function in equation 1.7 shows elasticity parameters (β_1 to β_6) which represent the output elasticities of the various inputs (SEED, K, LAB, FERT) as well as the agglomeration indexes FA and FD. In the model, the output elasticities are functions of the various inputs used. The first-order coefficient is interpreted as elasticities of the output with respect to the inputs used when we normalize the input and output variables by their respective means (Onumah *et al.,* 2010). The sum of the elasticities is the returns to scale or the estimated scale elasticity (ε). Returns to scale is the percentage change in output resulting from a percentage change in all the input factors. The estimated scale elasticity for the industry demonstrates either increasing returns to scale ($\varepsilon > 1$), decreasing returns to scale ($\varepsilon < 1$) or constant returns to scale ($\varepsilon = 1$).

Hypotheses Tests for Model Specifications and Statistical Assumptions

The main test of the study is that increased levels of knowledge and information spillovers could reduce the errors made in decision-making and this could lead to more technically efficient and productive soybean farming. This is evidenced by the elasticities associated with the output variable estimates for both the production frontier and efficiency models.
The study investigated some hypotheses tests for model specifications (Table 1.3) employing the generalized likelihood ratio test, the statistic specified as:

$$LR = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}] \tag{1.9}$$

where $L(H_1)$ and $L(H_0)$ represent the values of likelihood function under the alternative and null hypotheses respectively (Onumah *et al.,* 2010). *LR* has an approximate Chi-square or mixed Chi-square distribution and this is conditional on the null hypothesis being true with a degree of freedom equal to the number of parameters assumed to be zero in the null hypothesis (Coelli, 1995).
The hypothesis test is carried out to determine whether the functional form adopted for the data, which is the stochastic frontier model, is the best suited representation of the data, especially in comparison to the Cobb-Douglas functional form, and whether the conventional and exogenous input variables in the efficiency model can explain the technical efficiency (Coelli, 1995; Etwire *et al.,* 2013). These tests are necessitated by the distributions in the error term.

The hypotheses to be tested include the following:

1. The test hypothesizes that the stochastic frontier model is better suited for the data analysis. The null hypothesis is that the Cobb-Douglas production function is the best fit for the data.
2. The null hypothesis is that inefficiency effects are absent from the model at every level. The alternative hypothesis is that there are inefficiency effects within the production function at every stage.
3. The null hypothesis is that inefficiency effects are non-stochastic, contrary to *a priori* expectations of stochasticity in the in-efficiency. Conversely, the alternative hypothesis states that inefficiency effects are stochastic.
4. The null hypothesis is that the simpler half-normal distribution adequately represents the data, given the specifications of the generalized truncated-normal model. The alternative hypothesis is that the simpler half-normal distribution does not adequately represent the data.
5. Specific farm factors are hypothesized to influence inefficiency, however the null hypothesis states that inefficiency is not in-fluenced by the farm factors.
6. The null hypothesis is that agglomeration externalities (FA and FD) have no effect on efficiency and productivity. The alter-native hypothesis is that FA and FD influence efficiency and productivity.

Table 1.3: Tests of hypotheses for model specifications and statistical assumptions

Null Hypothesis	Alternative hypothesis
H_0: $\beta ij = 0$	H_A: $\beta ij \neq 0$
H_0: $\gamma = \delta_0 = \delta_1 = \cdots = \delta_{10} = 0$	H_A: $\gamma \neq \delta_0 \neq \delta_1 \neq \cdots \neq \delta_{10} \neq 0$
H_0: $\gamma = 0$	H_A: $\gamma \neq 0$
H_0: $\delta_0 = \delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	H_A: $\delta_0 \neq \delta_1 \neq \delta_2 \neq \cdots \neq \delta_{10} \neq 0$
H_0: $\delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	H_A: $\delta_1 \neq \delta_2 \neq \cdots \neq \delta_{10} \neq 0$
H_0: $\delta_9 = \delta_{10} = 0$	H_A: $\delta_9 \neq \delta_{10} \neq 0$

Source: Adapted from Onumah et al., 2010.

The Ox-SFAMB version 3.40 software was used to obtain the MLEs for the different parameters and was also used to analyze the so-cio-economic and demographic characteristics of the soybean farmers.

RESULTS AND DISCUSSION

Socio-Economic Characteristics of Soybean Farmers in Ghana

Of the 393 farmers, 196 were from the Upper East Region and 197 from the Upper West Region. 193 (49.1%) belonged to farmer associations and 200 (50.9%) did not belong to any farmer association and so would usually ply their farming activities independent of any farmer groups.

The respondent farmers were made up of 148 males and 245 females. Females seem to participate more in soybean farming partly because it is considered as a crop mainly grown by women and also because of the many interventions that have provided aid to women vis-à-vis soybean production (MEDA, 2017) creating an incentive for women-participation and involvement.

The majority of the farmers are married (76%) confirming the findings of Etwire *et al.* (2013) and Okpachu *et al.* (2014) that marriage among farmers in Northern Ghana is high and this so not only because it is an important social obligation, but also because it pro-vides a source of family labour and an opportunity for women farmers to own lands.

The majority of the farmers are Muslims (81.8%) and a high proportion of them have had little or no formal education which is a farmer demographic that is typical of the farming landscape in Ghana, as described in the GLSS 6 (GSS, 2014). The results also reveal that the average number of years spent in formal education by the farmers is 1.9 years; this is quite low. The means are lower than the mean number of years of education of 2.3 years as estimated by Mohammed *et al.* (2016) for farmers in the Northern Region of Ghana. Etwire *et al.* (2013) explain that farm households consider formal education as uncomplimentary to farming and so deem it a threat to their farming activities. This dynamic can be inimical to the adoption of new farming techniques and seed varieties as some appreciable level of education is needed to facilitate this.

The mean age of the farmers was 41.8. Incidentally, a study carried out by Mohammed *et al.* in 2016 gives the average age of soy-bean farmers in northern Ghana as 39 years, indicating that the sector is mostly dominated by middle-aged farmers. Etwire *et al.* (2013) state average ages of male and female farmers as 44 percent and 36 percent respectively, implying that current soybean farmers may still be able to actively cultivate the crop for the next two or three decades. The average household size of the farmers was 7.67. The household comprises adult males and females, and children not yet 18 years old. The data also shows that the mean number of adult males, adult females and children per household are 1.48, 2.14 and 3.82 respectively.

The average number of years of general farming (years of experience in the farming sector) was 6.97. The study also tried to ascer-tain the number of years of soybean farming by the farmers, recording mean years of experience in soybean farming as 4.88. This is an adequate amount of experience and should have positive implications on their output since they understand better the intricacies of farming (Okpachu *et al.,* 2014).

About 77.8 percent of the farmers received extension services during the 2016 farming season while 22.15 percent did not have any interaction with extension officers. The mean number of times farmers were visited by extension agents was 2.3. The more interactions farmers have with extension agents, the more they are able to access advice related to farming practices, input and market information (Associates for Change, 2012).

Analysis of Agglomeration Externalities

Analyses were carried out on the data collected, to ascertain the agglomeration externalities. The analysis show that of the 393 farmers interviewed, 193 (49.1%) belong to farmer associations such as Farmer Based Organizations, cooperatives, groups set up by NGOs or the farmers themselves, among others. Two hundred (50.9%) of the farmers did not belong to any farmer agglomerate and operated their farming activities as independent farmers.

Farmers who form or join farmer groups would usually do so to pull together ideas, for reasons of synergy and other positive agglomeration externalities that culminate from like-mindedness (Etwire *et al.,* 2013; Battese and Tveteras, 2006). They would also form groups to improve the economies of scale. Battese and Tveteras (2006) found that the formation of groups, leading to increased industry sizes, leads to increases in output and efficiency. It is therefore not very encouraging the current statistic of soybean farmers who belong to farmer groups or associations.

The study also sought to identify the farm densities within the farmer agglomerates, based on the location and proximity of farms to each other. From Battese and Tveteras (2006), there is an assertion that farm density is closely linked to the sharing of industry infrastructure among farmers who locate their farms close to each other, and that opportunities arise to exploit external economies of scale towards increasing productivity and efficiency. Identifying these farm densities was carried out only for farmers who belong to farmer associations. The results of the analysis identified 5 categories of farm densities among the 193 soybean farms that belong to farmers in farmer associations. The parameter, Farm Density (FD), was measured by the number of farms within a square kilometre.

The analysis identified Farm Densities of 21 farms, 43 farms, 40 farms, 32 farms and 28 farms; 8 percent, 19 percent, 41 percent, 17 percent and 15 percent of the FA farms belonged respectively to these FDs.

The greater the farm density, the greater the agglomeration externalities (Battese and Tveteras, 2006) and the stronger the agglomeration economy that is established (de Vor and de Groot, 2008). As such, farm densities of 43 and 40 farms should have higher levels of agglomeration externalities such as knowledge spillovers than farms belonging to lower farm densities due to increased frequencies of interactions between farmers and also lobbying opportunities that are made available to these farmers due to their size (de Vor and de Groot, 2008).

The findings (Table 1.4) reveal that the majority of FA farmers (88.6%) listed knowledge on farming techniques as the most impactful positive externality arising from belonging to farmer associations. They also recognized advice on soybean farming (83.4%) and information on labour and access to an available labour pool (71.5%) as very key agglomeration externalities. This is in line with the findings of Duranton and Puga (2004) that the most significant sources of agglomeration externalities include labour supply, demand matching and knowledge spillovers. About 68.9 percent alluded to infrastructure development being a merit of agglomeration.

The farmers also identified some negative externalities that arise from farmer agglomerations. In their paper, Larue and Latruffe (2008) state that negative externalities need to be considered in the analysis of the effects of agglomeration externalities. The negative externality ranked highest by the farmers is the unfavourable competition (62.7%) that arises as a result of proximity to each other and belonging to close knit farmer groups.

Other negative externalities that the findings of the study revealed are problems of water shortage due to pressure exertions on limited water sources by large groups of farmers, and rising incidence of water pollution. Other negative consequences of agglomeration were identified by farmers as theft and incidence of crop pests and diseases.

Table 1.4: Agglomeration externalities in the soybean sector

Agglomeration externality	Percentage (%)
Positive Externalities:	
Knowledge on soybean farming techniques	88.6
Advice on soybean farming	83.4
Information on and access to labour (labour pooling)	71.5
Industry infrastructure	68.9
Negative Externalities:	
Unfavourable competition	62.7
Water unavailability	57
Water pollution	50.3
Theft	32.6
Incidence of crop pests	27.5
Incidence of crop diseases	17.1

Source: Survey data, 2017

Descriptive Findings of Frontier Model Variables

Productivity of the farmers was a key focus of this survey. The study investigated productivity issues arising from outputs that are churned out per unit input used in the soybean sector. The results of the analysis revealed some estimates for output and input variables for both FA and non-FA farmers.

The output of the farmers for the 2016 season was computed at an average of 354 kilograms. The quantity of seed used by soybean farmers ranged from a minimum of 0.9 Kg/Ha to 54 Kg/Ha. The findings revealed that mean seed quantities planted by farmers is 9.45 kilograms. This is below the mean seed quantity of 12.7 kilograms applied per hectare as revealed by Mohammed *et al.* (2016) for soybean farming in the Northern Region of Ghana. Mean quantities used of inoculant, weedicide and compost were 25.45 kilograms, 15.15 kilograms and 59.05 kilograms respectively (Table 1.5). Mean amounts of weedicides used per season confirm the findings of Mohammed *et al.* (2016) of 15.2 kilograms per hectare.

Mean amounts of labour employed by soybean farmers was 30.75 person-days. Compared to the situation in Vietnam, which is one of the highest producers of soybean in the world, Khai and Yabe (2013) reveal a mean of 57.03 person-days leading to average output levels of 1,788.76 kilograms for the 2012 soybean farming season. The mean number of person-days employed per farm for the Northern region, per the report of Mohammed *et al.* (2016), was 41.4.

From the findings of the study, the average farm size is 0.4 hectares with farm sizes ranging from 0.04 to 2.43 hectares for soybean farmers in both the Upper East and Upper West Regions. The findings of Etwire *et al.* (2013) of mean farm sizes of 0.4 for soybean farms in the Northern Region show that farm sizes are about the same across the three northern regions of Ghana, averaging about 0.4 hectares per soybean farm.

Table 1.5: Summary statistics on productivity estimates of soybean farmers

Variables	Minimum	Maximum	Mean	Std. Dev.
Output (Kg)	60	800	354	154.655
Seed quantity (Kg)	0.9	54	9.45	6.87
Inoculant (Kg)	0	100	25.45	3.5397
Weedicides/herbicides (litres)	0	60	15.15	12.155
Compost (Kg)	0	500	59.05	109.855
Labour (person-days)	6	60	30.75	14.3
Farm size (Ha)	0.04	2.43	0.4	0.305

Source: Survey data, 2017

Hypotheses Tests for Model Specifications and Statistical Assumption

The results of the hypotheses tests presented in Table 1.6 show that the first null hypothesis that states the Cobb-Douglas function is an adequate representation for the data (by stating that the coefficients of the second-order variables add up to zero) is rejected. The translog stochastic function is better suited to the data. The null hypothesis stating that inefficiency effects are not stochastic is also rejected. The null hypothesis for the third test is also rejected showing therefore that the Ordinary Least Square function is not the best model of estimation for the data. For the fourth hypothesis, the null hypothesis is rejected for the alternative - the intercepts and coefficients associated with the efficiency model do not add up to zero. This shows that inefficiency variables influence technical efficiency.

Table 1.6: Hypotheses tests for model specification

Null hypothesis	Log-likelihood value	Test statistics (λ)	Critical value ($\lambda^2_{0.001}$)	Decision
H_0: $\beta ij = 0$	26.42	22.80	18.47	Reject H_0
H_0: $\gamma = \delta_0 = \delta_1 = \cdots = \delta_{10} = 0$	50.69	38.23[a]	20.52	Reject H_0
H_0: $\gamma = 0$	275.62	35.44[a]	10.83	Reject H_0
H_0: $\delta_0 = \delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	50.70	48.55	22.46	Reject H_0
H_0: $\delta_1 = \delta_2 = \cdots = \delta_{10} = 0$	50.56	48.28	20.52	Reject H_0
H_0: $\delta_9 = \delta_{10} = 0$	251.13	32.15	16.71	Reject H_0

[a] Values of test of one-sided error from the Ox output.

The fifth hypothesis that assumes all coefficients in the inefficiency model (with the exception of the constant term) are zero is also rejected. This shows that the collective effects of factors of farm inefficiency play a significant role in explaining variations in the soybean sector. The sixth hypothesis is the test of FA and FD. The coefficients of FA and FD in the efficiency model do not add up to zero and so the null hypothesis is rejected.

Productivity Estimates of the Stochastic Frontier

The Maximum-Likelihood Estimates (MLE) of the stochastic frontier translog model are presented in Table 1.7. The coefficients of the input variables are explained as elasticities to describe the production of soybean vis-à-vis the individual inputs of production.

Results show positive coefficients for all the input variables, including those of the agglomeration variables, FA and FD. They are all statistically significant indicating significant effect of the input variables on soybean production Ghana.

The results show that output elasticities for the input variables SEED, CAPITAL, LABOUR and FERT have positive significant coefficients indicating influence of statistical significance on the dependent variable, productivity. A percentage increase in seed-use, capital, labour and fertilizer-use (inoculant-use) will increase soybean output by 0.14 percent, 0.14 percent, 0.28 percent and 0.41 percent respectively. With an output elasticity of 0.41, inoculant (captured as FERT) is the most important input among the four conventional input variables and thus has the highest impact on productivity. Labour is the second most important input in terms of the frontier output elasticity with a value of 0.28 indicating significant impact on the production frontier.

FA and FD show a positive relationship with productivity, statistically significant at 5 and 10 percent respectively. The elasticity of frontier output with respect to FA and FD are 1.02 and 0.03 indicating that FA (farmers belonging to groups), which is an indicator of the size of industry, has the greatest effect on the production frontier. This is in line with findings by Battese and Tveteras (2006) for the effect of FA/industry size on productivity. An increase in FA and FD by 1 percent will lead to respective increases of 1.02 percent and 0.03 percent in the output. Thus an increase in the number of farmers forming or joining agglomerates and an increase in the number of farms per square kilometer will lead to increases in output.

The positive elasticities associated with FD and FA show that there are positive externalities associated with farm density and farmer associations and these are statistically significant. The sum of the output elasticities is 0.98 indicating diminishing returns to scale. This result corroborates the findings of Mohammed *et al.* (2016) for the soybean sector in the Northern Region. They report returns to scale of 0.79 indicating diminishing returns to scale. This means therefore that if input factors are increased by the same proportion, the increase in output will be less than proportionate to increases in the input variables. Therefore, if Ghana's soybean sector increases all of its factor inputs by 1 percent, soybean production would increase by 0.98 percent. Farmers are therefore better off when they reduce their output levels.

Table 1.7: Estimates of the stochastic frontier model (Productivity estimates)

	Coefficient	p - values
Constant	0.386389**	0.017
LnSEED	0.139101***	0.000
LnK	0.141429***	0.001
LnLAB	0.282621***	0.000
LnFERT	0.413061***	0.000
FD	0.0276757**	0.025
FA	1.022346*	0.086
RTS	0.98	

***, **, * indicate significance at 1%, 5% and 10% respectively

Technical Efficiency Estimate Scores

The results of the analysis show that technical efficiencies for soybean farms in the Upper East and Upper West Regions range from 0.15 to 0.99 (Figure 1.1). This conforms to the findings of Etwire *et al.* (2013) which gave a technical efficiency range of between 0.11 and 0.99 for soybean farms in the Northern Region. This wide variation in technical efficiency scores indicates the presence of varying levels of resource utilization among soybean farmers. Diverse managerial and decision-making patterns also contribute to the vast differences in the efficiency scores across soybean farms in the two regions. The soybean sector thus demonstrates an uneven distribution of farmers across different technical efficiency scores. About 35.3 percent of the soybean farms operate at efficiency levels of 60 percent and above with about 19.5 percent operating above efficiency levels of 80 percent. This group can be said to be the most technical efficient in the sector. An estimated 55 percent of the soybean farms, being the least efficient, were found to be operating at efficiency levels of below 50 percent.

The mean technical efficiency index for soybean farms was estimated at 0.52 indicating about 52 percent efficiency. This shows that averagely, soybean farmers produced 52 percent of the potential (stochastic) frontier output and fell short of the frontier by 0.48 points. Therefore, given the technology and input levels available to soybean farmers, 48 percent of technical potential output is not realized. There is therefore about 48 percent room for improvement for the average soybean farmer to increase their output while maintaining current levels of technology and input-use. Etwire *et al.* (2013) and Mohammed *et al.* (2016) report mean efficiency levels of 53 percent and 54.2 percent respectively for soybean farms in Northern Ghana.

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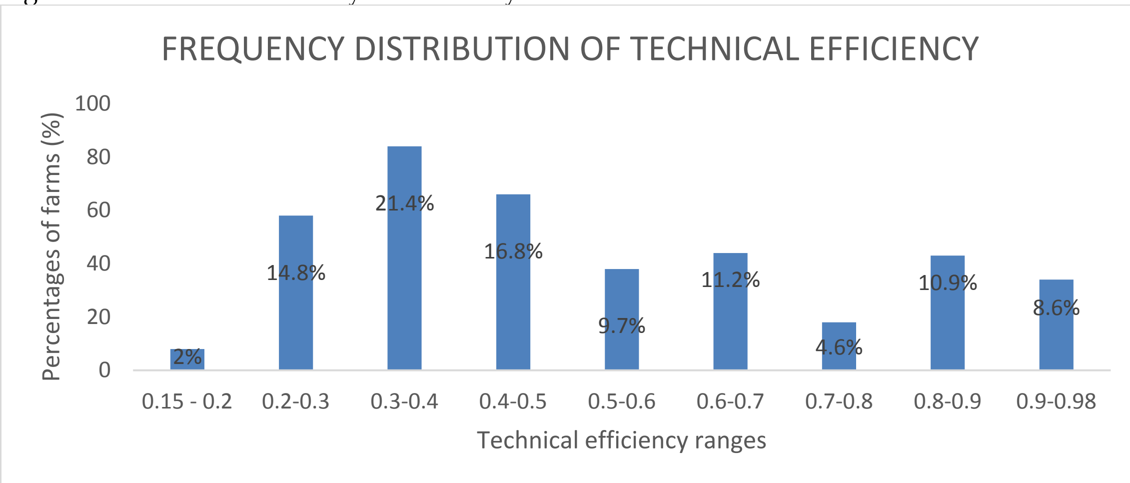
Figure 1.1: Technical efficiency scores of soybean farmers



Source: Survey data computations, 2017.

The results indicate comparatively high inefficiency in soybean production in the northern part of Ghana, especially in the Upper East and Upper West Regions. The high inefficiency levels could be as a result of non-farm employment, and inadequate levels of education, farm experience and degree of specialization (Olayiwola, 2013).

Olayiwola (2013) reports a mean efficiency score of 87 percent for smallholder soybean farms in Nigeria, indicating a comparatively higher technical efficiency score statistic in the soybean sector in Nigeria. There is considerable potential for improving the productivity of soybean farms given the current inputs and technology available. This will enable the farmers to reduce costs of production and increase their output levels.

Determinants of Technical Efficiency

The study examined the determinants of technical efficiency in the soybean sector to establish a basis for informing policy on the actions to be taken to improve the technical efficiency of the farmers. Table 1.8 presents the coefficients of the inefficiency variables. The signs and significance of the parameter estimates have implications for policy concerns. A positive estimate indicates a positive impact on the level of technical inefficiency.

The results show positive statistically significant coefficients for Age of farmer, Gender and FA. This shows that older farmers are less technically efficient than younger ones and this could be as a result of younger farmers having a more progressive attitude to new technologies and farming innovations (Onumah *et al.,* 2010). The findings are in line with those of Coelli and Battese (1996) that explained that this occurrence could be due to the conservative nature of older males and their unwillingness to adopt new technology. These findings are also in line with those of Onumah *et al.* (2010) and Shaheen *et al.* (2011) whose findings of fish farmers and cauliflower growers respectively revealed that younger farmers are more technically efficient than older farmers.

Table 1.8: Efficiency model estimates

	Coefficient	p - values
Constant	0.150335	0.695
MARSTAT	0.201916	0.124
EXP	-0.0182781	0.255
EXPSoy	-0.0125825	0.630
AGE	0.00987458*	0.088
GEN	0.356142**	0.013
EXTNum	-0.0871227*	0.094
HHS	-0.0226126	0.238
EDUCYrs	0.00871641	0.484
FA	5.97356*	0.074
FD	-0.276019*	0.097

Source: Analysis of survey data, 2017.
**, * indicate significance at 5% and 10% respectively

A positive coefficient for the gender dummy is positively significant indicating therefore that female farmers are more technically efficient than male farmers. This confirms the findings of Mohammed *et al.* (2016) and could be as a result of the many initiatives spearheaded by NGOs and government to empower women farmers (MEDA, 2017) by providing them with inputs and other resources.

The coefficient of the variables EXTNum (Number of extension agent visits) and HHS (Household size) were negative with the coefficient of EXTNum being statistically so. This indicates therefore that an increase in the frequency of farmer-extension agent interactions leads to higher efficiency of farmers. Farmers who interact more with extension agents are therefore more efficient than farmers who do not interact with them as much. Perhaps this is so because new methods and technologies of farming are introduced to the farmers and the more regular these interactions, the better the rate of adoption. The findings of Dhebibi *et al.* (2007) and Ogundari (2013) conform to the findings of this study and explain that as extension agents serve as a link between farmers and researchers, they are conduits through which new innovations in farming methods are introduced to farmers.

The coefficient of FD is significantly negative indicating therefore that farm concentration is positively related to technical efficiency. Hence, increase in farm density leads to increase in technical efficiency. This conforms to the findings of Battese and Tveteras (2006) whose findings confirmed *a priori* expectations of increase in technical efficiency with increase in farm density. This is as a result of the positive externalities that arise from farm proximity to each other, such as input-sharing - likely to lead to reduction in cost, knowledge and information spillovers that may inform farmers on more efficient methods of production.

The coefficient of FA is significantly positive suggesting that farmers who belong to farmer associations tend to be less efficient than those who do not. This is in contrast with the findings of Battese and Tveteras (2006) whose findings revealed that industry size (captured as FA in this study) has a positive influence on efficiency. The findings of this study with respect to the effects of FA could be due to farmers not utilizing efficiently the opportunities that are presented them by virtue of them belonging to groups. For example, time wasted chatting or pursuing other non-profitable ventures could tell negatively on their efficiency. The result could also mean that the negative externalities that arise from farmer agglomeration could be accounting for these results. These could include the dissemination of harmful advice or information pertaining to farmers' methods of farming (Battese and Tveteras, 2006) and this could influence negatively their methods of farming.

Conclusion

The main objective of this study has been to assess the influence of agglomeration externalities on the productivity and technical efficiency of soybean farms in Ghana. The results from data analysis indicate a significant presence of such externalities in the soybean production sector. In light of supporting empirical evidence from hypotheses tests, the stochastic frontier and technical efficiency models used for the estimation of the productivity and efficiency of soybean farms are the most appropriate for these measurements, the results of which form the underpinning conclusions of the paper.
Internal returns to scale and agglomeration externalities are seen to be the main factors explaining the differences in output levels and productive performance. Input factors such as seed, capital, labour and more significantly, inoculants (fertilizer), are seen to have a positive impact on productivity, indicating that increases in the levels of use by farmers would lead to efficient production methods and significantly higher output levels. Diminishing returns to scale in the soybean sector also indicates less than proportionate increases in output with increases in inputs, indicating ineffective resource combination among the farmers, leading to farmers being better off producing less. These high levels of inefficiency are further emphasized by the low mean efficiency level which is way below optimum efficiency levels. This finding is corroborated by the findings of similar studies on technical efficiency levels of soybean farms in Ghana. Output levels could increase by improving efficiency scores by 48 percent to achieve the 4.5 MT/Ha potential, with current input levels.
Some exogenous factors identified to have significant implications on technical efficiency include the age (younger farmers are more efficient) and gender (females are more efficient) of the farmers. Efficiency was found to increase with increase in frequency of visits of extension agents to soybean farms, leading to the strong recommendation for more interactions via visits, workshops, etcetera.
The results for the agglomeration indexes show that FA and FD have a significant positive influence on the production function. Increases in industry size through farm density (farm concentration or proximity of farms to each other) and by farmers belonging to farmer groups therefore increase the productivity of soybean farmers. The technical efficiency of soybean farmers increases with increases in farm density and this could be attributed to the positive externalities that arise from agglomerations. Farmers who belong to farmer associations were found to be less efficient than those who are not members of farmer agglomerates, and this could be due to the negative externalities that arise among such groupings, such as the dissemination of bad farming advice or information.
This study brings to the fore issues pertaining to productivity and technical efficiency in the soybean sector and the implications of agglomeration externalities on these parameters, and proposes that more extensive studies are carried out on the effects of biological and biophysical differences, farm-specific factors and regional industry infrastructure on differences in productivity, with respect to the agglomeration externalities, that exist in the soybean and other agricultural sectors.

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References

[1] A. Markusen, “Sticky Places in Slippery Spaces: A Typology of Industrial Districts,” *Economic Geography*, vol. 72, no. 3, pp. 293 – 313, 1996.
[2] A.N. Maciente, “The Determinants of Agglomeration in Brazil: Input-Output, Labour and Knowledge Externalities,” PhD dissertation, University of Illinois, Urbana – Champaign, 2013.
[3] A.S. Okpachu, O.G. Okpachu and J.K. Obijesi, “The Impact of Education on Agricultural Productivity of Small Scale Rural Female Maize Farmers in Potiskum Local Government, Yobe State: A Panacea for Rural Economic Development in Nigeria,” *International Journal of Research in Agriculture and Food Sciences.* 2014.
[4] Associates for Change (AfC), “The Ghana Food Security Research with a Focus on the Upper West Region," Submitted to Mennonite Economic Development and Associates, 2012. unpublished.
[5] B.L. Dhebibi, M. Elloumi and E.B. Messaoud “Measurement and Sources of Technical Inefficiency in the Tunisian Citrus-Growing Sector,” *Conference, Mediterranean Scientists, Agro-Food Social Seminar, EAAE*, 2007.
[6] C. Burnside, “Production Frontier Regressions, Returns to Scale, and Externalities,” *Journal of Monetary Economics*, vol. 37, no. 2, pp. 177 – 201, 1996.
[7] D. Puga, “The Magnitude and Causes of Agglomeration Economies,” *Journal of Regional Science*, IMDEA Social Sciences and CEPR. 2009.
[8] D.J. Aigner, C.A.K. Lovell and P. Schmidt, “Formulation and Estimation of Stochastic Frontier Production Function Models,” *Journal of Econometrics*, no. 6, pp. 21 – 27, 1977.
[9] E.E. Onumah, B. Brummer and G. Horstgen – Schwark, “Elements Which Delimitate Technical Efficiency of Fish Farms in Ghana,” *Journal of the World Aquaculture Society.* 2010.
[10] F. de Vor and H.L.F. de Groot, “Agglomeration Externalities and Localized Employment Growth,” Tinbergen Institute, V.U University of Amsterdam, The Netherlands, 1993.
[11] G. Duranton and D. Puga, *Micro-Foundations of Urban Agglomeration Economics.* In J.V. Henderson and J.F. Thisse. Handbook of Regional and

Urban Economics, 2004.

[12] G.E. Battese and G.S. Corra, "Estimation of a Frontier Model: with Application to the Pastoral Zone of Eastern Australia," *Australian Journal of Agricultural Economics*, no. 21, pp. 167 – 179, 1977.

[13] G.E. Battese and R. Tveteras, "Technical Change and Productive Inefficiency Change in Norwegian Salmon Farming: The Influence of Regional Agglomeration Externalities," *Journal of Regional Science*, vol. 46, no. 4, pp. 605 – 625, 2006.

[14] G.E. Battese and T.J. Coelli, "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production for Panel Data," *Empirical Economies*, no. 20, pp. 325 – 332, 1995.

[15] Ghana Statistical Service (GSS), *2010 Population Housing Census: National Analytical Report*, *Accra.* 2013.

[16] Ghana Statistical Service (GSS), *Poverty Profile in Ghana (2005 – 2013).* Ghana Living Standards Survey Round 6 (GLSS 6), 2014.

[17] H.V. Khai and M. Yabe, "Analysis of Productive Efficiency of Soybean Production in the Mekong Delta of Viet Nam," *Journal of Agriculture*, Jyushu University, 2013.

[18] J.M. Antle, "Human Capital, Infrastructure and Productivity of Indian Rice Farmers," *Journal of Development Economics*, 1984.

[19] J.V. Henderson, Z. Shalizi and A.J. Venables, "Geography and Development," *Journal of Economic Geography*, vol. 1, no. 1, pp. 81 – 105, 2001.

[20] K. Ogundari, "Crop Diversification and Technical Efficiency in Food Crop Production: A Study of Peasant Farmers in Nigeria," *International Journal of Social Economics*, vol. 40, no. 3, pp. 267 – 287, 2013.

[21] Mennonite Economic Development Associated (MEDA), http://www.meda.org/about-meda.html. 2017.

[22] Ministry of Food and Agriculture (MoFA), *Annual Report: Policy Planning, Monitoring and Evaluation Directorate.* Accra, Ghana. 2011.

[23] O.O. Olayiwola, "Technical Efficiency of Soyabean Production in Ijebu – Ode Local Government Area of Ogun State, Nigeria," *International Monthly Refereed Journal of Research in Management and Technology*, vol. 2, pp. 7 – 13, 2013.

[24] P.M. Etwire, E. Martey and W. Dogbe, "Technical Efficiency of Soybean Farms and its Determinants in Saboba and Chereponi Districts of Northern Ghana: A Stochastic Frontier Approach," 2013.

[25] S.A.R. Mohammed, S. Al-hassan and D.P.K. Amegashie, "Technical Efficiency of Soybean Farmers in the Northern Region of Ghana," *ADRRI Journal of Agriculture and Food Sciences*, vol. 2, no. 11 (2), pp. 20 – 38, 2016.

[26] S. Larue and L. Latruffe, "Agglomeration Externalities and Technical Efficiency in Pig Production," *European Association of Agricultural Economists (EAAE)*, 2008.

[27] S. Shaheen, M.H. Sial, G. Sarwar and R. Munir, "Nexus Between Human Capital and Technical Efficiency of Cauliflower Growers in Soon Valley, Punjab: A Panel Data Analysis," *International Journal of Humanities and Social Sciences*, vol. 1, no. 14, pp. 129 – 135, 2011.

[28] S.S. Rosenthal and W.C. Strange, "The Determinants of Agglomeration," *Journal of Urban Economics*, vol. 50, no. 2, pp. 191 – 229, 2001.

[29] T.J. Coelli, "Estimators and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis," *Journal pf Productivity Analysis*, vol. 6, no. 3, pp. 247 – 268, 1995.

[30] T.J. Coelli and G.E. Battese, "Identification of Factors Which Influence the Technical Inefficiency of Indian Farmers," *Australian Journal of Agricultural Economics*, no. 40, pp. 103 – 128, 1996.

[31] W. Meeusen and J. van den Broeck, "Efficiency Estimation from Cobb-Douglas and Production Functions with Composed Error," *International Economic Review; Impact of Financial Sector Liberalization on the Poor (IFLIP)*, no. 1, pp. 1 – 5, 1977.