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Stochastic Frontier Modeling of Maize Production in Brong-Ahafo Region of Ghana

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Abstract

Maize is a major staple crop in Ghana which needs to be produced optimally towards food security and commercialization. In relation to this the study adopts the stochastic frontier model to analyze technical efficiency of maize farms in the Brong Ahafo Region of Ghana using a cross sectional data of 232 farms. The findings demonstrate that the input variables scaled per hectare: seed, herbicide, labor and cost of intermediate input influence maize output positively at a decreasing returns to scale. The study further finds that maize producers realize 83% of the frontier output averagely and there is the possibility to increase maize output by 17% at the given technology and input levels in the short run through the adoption of the best farm practices. The study concludes that producer specific factors impede the full potential of the farmers and the inefficiency effects can be mitigated by focusing on policies that enhances the use of best farm practices.

Key words

Maize, frontier, technical efficiency, productivity, returns to scale.

Introduction

Maize is the most important cereal and staple food crop for more than 1.2 billion people in sub-Saharan Africa (SSA) (IITA, 2013). Worldwide production of maize is 785 million tons, with the largest producer, the United States, producing 42%. Africa produces 6.5% and the largest African producer is Nigeria with nearly 8 million tons, followed by South Africa (IITA, 2013). Ghana produces about 2 million tons of maize in the year 2010 (MoFA, 2010). Average maize yields among the developing countries, as an aggregate, are about one-third of those of the major maize producers. China, who is among the largest maize producing countries in the world produces around 5 tons/ha while in Ghana it stands at around 1.7 tons/ha against achievable yields of 5-6 tons/ha. This is compared to realized average yield of 9 tons/ha in the United States, the highest world producer. Maize as a major staple food in Ghana facilitates food security and provides employment opportunities to generate income for most farming households. It also serves as raw material for industrial purposes (WABS Consulting Ltd., 2008). Growth in population, per capita income and the production links from other related economic activities requires annual maize output to grow by 2.6% between 2010 to 2015 (MiDA, 2007). Again, Brong Ahafo Region is well endowed for maize production and if maize production intensifies, it can contribute immensely to increase maize output in the country.

Although research has come out with new ways of cultivating maize for maximum production; constraints on use and access to technology are among the factors contributing to low yields and productivity in maize production in the region. The gap between potential yield and the actual yield has been estimated at 200-300% for staple crops (Al-hassan & Diao, 2007). The average yield of 1.7 tons/ha against the achievable yield of 5-6 tons per hectare of land in the region presents opportunity for growth through gains in productivity. This study, therefore seeks to determine the drivers of maize output through productivity and technical efficiency gains in the Brong-Ahafo Region of Ghana. Belbase and Grabowski (1985) indicate that it is more cost-effective to improve efficiency than introducing new technologies if farmers are not optimizing the use of existing ones. Specifically, the study tries to estimate the partial productivities of the individual input factors, the individual technical efficiency scores and the determinants of technical inefficiency. The estimates of the productivities of the input factors to maize output contribute to revealing the relationships between the inputs to output to adjust the inputs efficiently in the maize production process. This also determines the scale elasticity of production which informs policy on how to produce efficiently given the returns to scale in the production process. The understanding of the level of technical efficiency and its determinants is needed to know the existing gap of maize output from the frontier output at the given technology to inform policy interventions to increase output in the short run without employing additional resources. Production of maize from technological progress will increase output at the given input level to benefit the producer and the average consumer to improve the standard of living.

Materials and methods

1. Study area

The study is based on farm level data on maize cultivation in the Brong-Ahafo Region of Ghana. The study uses data from both the major and minor seasons. Maize cultivation in the major season usually occurs from March to June and a short dry-spell occurs in July is used for harvesting and sun-drying. This is followed by a minor season from August to November. Nkoranza, Kintampo North and South, Wenchi Districts are in the transition zone of Ghana where soils are deep and friable and well drained, and there is less dense forest cover. Districts such as Sunyani West and Berekum Districts occur in the semi-deciduous forest zone which also satisfy the weather requirements for maize production and also permit two season maize production. The average annual rainfall and temperature are 1,300 mm and 270c respectively to promote maize cultivation.

2. Theoretical framework for Stochastic Production Frontier Model (SFP)

The stochastic frontier approach for crossectional data is adopted for this study. The model is represented in equation (1):

$$y_i = f(x_i;\beta).\exp(v_i).\exp(u_i) \quad (1)$$

The actual output y_i produced by the *i-th* farmer depends on the vector of input factors denoted by x_i. The actual output y_i deviates from the frontier output as a result of pure noise represented by v_i and inefficiency effects also represented by u_i. β represents the unknown true parameters of the production technology.

The technical efficiency of the *i-th* farm is given by equation (2):

$$TE_i = \frac{E(Y_i/x_i,u_i)}{E(Y_i/x_i,u_i=0)} = \frac{f(x_i\beta).\exp(v-u_i)}{f(x_i:\beta).\exp v_i} = \exp(-u_i) \quad (2)$$

And technical efficiency becomes;

$$TE_i = \exp(-u_i) \quad (3)$$

Thus the technical efficiency effects become $TE_i = E(\exp\{-u_i\} \mid \varepsilon_i)$ and the technical inefficiency effects are truncated at zero of the normal distribution with mean μ_i and a variance σ_u^2, u_i (μ_i, σ_u^2), where the mean is defined as $\mu_i = \delta z_i$. z_i, represents the exogenous variables and δ denotes the unknown estimates of the exogenous variables on technical inefficiency as employed by Battese and Coelli (1995). The application of FRONTIER 4.1 to an appropriate production model produces the ML estimate of the frontier model, the technical inefficiency function and the individual farm specific technical efficiency estimates. The estimates become unbiased unlike the two stage estimation procedure for incorporating exogenous variables in technical efficiency analysis (Kumbhakar and Lovell, 2000). The log likelihood function is parameterized in terms of $\sigma_2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$ (Battese, Corra, 1977). If $\gamma = 1$ it means that the deviations in output are as a result of technical inefficiency only whilst at the other extreme value of zero, indicates that technical inefficiency is absent and deviations in output are controlled by the distribution of the pure noise component. But if γ is in between zero and one it implies that output variability from the frontier is explained by both pure noise and technical inefficiency effects.

3. Empirical model specification

The translog production model is assumed for the deterministic part of the production frontier and it is specified as:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j Inx_{ji} + 0.5\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln x_{ji} Inx_{ki} + \varepsilon_i \quad (4)$$

β_j denotes the unknown true estimates of the *j-th* input in the production function. If $\beta_{jk} = 0$, then the translog stochastic frontier model reduces to the Cobb-Douglas model given as:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j Inx_{ji} + \varepsilon_i \quad (5)$$

The composed error term, includes the pure noise and technical inefficiency effects which are given as;

$$\varepsilon = v_i - u_i \qquad (6)$$

Y_i refers to output of maize produced, measured in kilograms per hectare[1]. This includes the aggregation of the two production seasons. X_{1i} refers to the quantity of seed per hectare (kg/ha) used by the *i-th* farm for the production year. X_{2i} refers to the total liters of herbicide per hectare used by the *i-th* farm during the production year. x_{3i} is captured based on the total labor input in man-days employed by the *i-th* farm per hectare during the production year[2]. Hired and family labours are assumed to be equally productive and are aggregated together. X_{4i} refers to the cost of intermediate inputs per hectare/mean including depreciated value of capital inputs such as cutlass, knapsack sprayer, cost of transportation and shelling and cost of ploughing for the *i-th* farm during the production year and measured in cedis. The sum total of the output elasticity from the input variables is the estimated scale elasticity (κ) which is defined as the percentage change in output as a result of 1% change in all input factors. When $(\kappa) \succ 1 \Rightarrow$ increasing returns to scale (IRS), $(\kappa) \prec 1 \Rightarrow$ decreasing returns to scale (DRS), and $(\kappa) = 1 \Rightarrow$ Constant returns to scale (CRS).

The technical inefficiency effects are explained by the exogenous variables in the model represented by equation (7);

$$q(z_j, \delta) = \delta_0 + \sum_{j=i}^{10} \delta_j z_i \qquad (7)$$

Where $\delta's$ are to be estimated coefficients of the technical inefficiency model and $z_i's$ are the exogenous explanatory variables and z_{1i} is the squared of the age of the farmers measured in years. z_{2i} denotes access to in-kind credit and farmers who used in-kind credit for the production year are assigned a value of 1 and zero otherwise. z_{3i} represents gender where by 1 is assigned for males and 0 for females. Z_{4i} Education, represents the maximum level of formal schooling of the farmer[3].

Z_{5i} represents the number of contact made by the farmer with the extension officer during the production year. Z_{6i} is represented as Dumplough where a farmer who ploughs the land before sowing for the production year is assigned a value of 1 and zero for those who did not plough Bkdistrict, farmers who belong to the Berekum district are assigned a value of 1 and 0 otherwise. This hypothesis is used to capture the differences in districts in relation to technical inefficiency. z_{8i} Nkdistrict, farmers who belong to the Nkoranza district are assigned a value of 1 and 0 otherwise. z_{9i} Kindistrict, farmers who belong to the Kintampo district are assigned a value of 1 and 0 for otherwise. z_{10i} Wendistrict, farmers who belong to the Wenchi district are assigned a value of 1 and 0 otherwise.

4. Statement of hypothesis

The following hypotheses are considered for investigation to the study; H_0: $\beta_{jk} = 0$, the coefficients of the second-order variables in the translog model are zero. The deterministic component of the frontier model reduces to the Cobb-Douglas model. H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \ldots \delta_{10} = 0$, the null hypothesis that technical inefficiency is absent at every level. The use of stochastic frontier model is justified for the analysis if technical inefficiency is present in the data. H_0: $\gamma = 0$, he null hypothesis specifies that inefficiency effects are non-stochastic and hence the model is appropriate to be estimated using the ordinary least squares method whilst nesting the exogenous factors into the mean output function. H_0: $\delta_0 = \delta_1 = \delta_2 = \ldots\delta_{10} = 0$ the null hypothesis that the simpler half normal model is an adequate representation of the inefficiency effects and hence the variance of the inefficiency effects are zero or the technical inefficiency effects are unrelated to the exogenous variables.

5. Data and sampling technique

A multi-stage sampling procedure is employed to obtain cross sectional data on the relevant variables for the study from 232 maize farms which is a fair representation of the maize farms in the region. The districts and communities are selected purposively due to their varying intensity of maize production at those areas. The selected

[1] The output and input variables are all normalized by their respective means to justify the first order parameters in the translog production model as elasticities.

[2] Man days for labour is calculated with the formula; one adult male working for one day (8 hours) equals one man day; one female and one child (< 18years) working for one day (8 hours) equals 0.75 and 0.5 man days respectively. The following researchers applied the above method for the calculation of man-days: Coelli and Battese (1996) and Onumah et al. (2010).

[3] Ranking of level of formal schooling for the study follows the study of Onumah & Acquah, (2011) is outlined as: None_0; Primary level_1; Junior Secondary/Middle School level_2; Senior Secondary/Vocational level_3;;Polytechnic level_4; University (bachelor) level_5.

districts are Sunyani West District, Wenchi East District, Berekum Municipal, Nkoranza South, Kintampo South and North Districts where the weather and soil conditions are favorable. Within each district three major maize producing communities are selected to select the maize farmers randomly to obtain a distribution of farmers as 50, 50, 47, 39 and 46 for Sunyani West, Nkoranza South, Kintampo North and South Wenchi and Berekum districts, respectively.

Results and discussion

1. Summary statistics of the output and the input variables

The quantity of seed used for the production year ranges between 4.85 to 43.13 kg/ha with a mean of 21.35 kg/ha and standard deviation of 6.54 kg/ha. Mean labour of 67.95 mandays/ha is applied which ranges from 13.06 to 236.86 mandays/ha while the farmers apply average herbicide of 8.57 liters also ranging from 0.10 to 40 liters. The mean cost of intermediate input per hectare is GHS 170.98 with minimum and maximum values of GHS 6.54 and GHS 1598.75, respectively. Maize output also ranges from 337.5 kg/ha to 6750 kg/ha with a mean of 1975kg/ha and standard deviation of 1027.74 (Table 1).

2. Testing of hypothesis

The null hypothesis that the Cob-Douglas model is suitable for the data is rejected at 1% level of significance in favor of the translog model. The implication for this is that the translog model is flexible to represent the production process better. The second hypothesis specifies that technical inefficiency is absent from the production process at all levels and it is rejected at 1% level of significance. The estimated gamma is 0.81 and it is significantly greater than zero and that the variations in the observed output from the frontier output are due to technical inefficiency and random noise but 80% of the variations in output are due to technical inefficiency. Therefore maize output variability is subject to farm specific factors that influence the efficiency to convert the inputs to output. The third hypothesis assumes that the technical inefficiency effects are non-stochastic but this hypothesis is rejected. This implies that the inefficiency effects are not unrelated to the exogenous variables but have a particular distribution which is determined by the exogenous variables. The fourth hypothesis accepts that the technical inefficiency effects are truncated with variable mean dependent upon the exogenous variables (Table 2).

Variable	Unit	Minimum	Mean	Maximum	SD
Output	Kilograms/ha	337.50	1957.51	6750.00	1027.74
Seed	Kilograms/ha	4.85	21.35	43.13	6.54
Labour	Man-days/ha	13.06	67.95	236.86	35.11
Herbicide	Liters/ha	0.10	8.57	40.00	5.82
Cost	Cedis/ha	6.54	170.98	1598.75	160.93

Source: Authors computation, 2012

Table 1: Summary statistics of output and input variables.

Null Hypothesis	Loglikelihood	Test Statistic (λ)	Critical Value	Decision
1. H_0: $\beta_{jk} = 0$	110.69	43.86***	23.21	Reject H_0
2. H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \dots \delta_{10} = 0$	-	26.61a	25.56	Reject H_0
3. H_0: $\gamma = 0$	102.06	6.49a**	5.41	Reject H_0
4. H_0: $\delta_0 = \delta_1 = \delta_2 = \dots \delta_{10} = 0$	98.81	20.12*	19.68	Reject H_0

Note: [a] Values of test of one sided error from the FRONTIER 4.1 Output file. The correct critical values for the hypotheses involving a γ follows a mixed chi-square distribution and are obtained from Kodde and Palm (1986), whilst the rest are obtained from the conventional chi-square table. *, ** Significant at 5% and 10% levels, respectively.

Source: Authors computation, 2012

Table 2: Hypothesis Test for model specification and statistical assumptions of stochastic frontier model.

3. Frontier estimates

The frontier estimates are presented in Table 3. However, discussion is done using the output elasticity presented in Table 4. The output elasticity for seed, herbicide, labour and cost of intermediate inputs which have been scaled per hectare are 0.25%, 0.21%, 0.02% and 0.23%, respectively. The results of the study are similar to the findings of Anupama et al. (2005) who find that labor, fertilizer and intermediate inputs contribute to output as 0.08%, 0.21% and 0.20%, respectively, in maize production in Tanzania. Seed makes the highest contribution to output in this study and a 1% increase in the input will cause a 0.25% increase in output and this is followed by cost of intermediate inputs which yields 0.23% of output for every 1 % investment in cost of intermediate inputs. However, labor contribution to output is the lowest and this contradicts with the findings of Chirwa (2007) study of small holder maize production in Southern Malawi which reveals that labor causes the most significant change in maize output because the production technology is more labor intensive.

The study further revealed that the scale elasticity is 0.71, to demonstrate that the maize farms in the area exhibits decreasing return to scale. This means if all the input variables with the exception of land increase by 1%, maize output would increase by 0.71%. Therefore the proportionate increase in output is less than the proportionate increase in the inputs. Hence scale diseconomies exist on the technology frontier and that the use of best farm practices to raise the productivity of both fixed and variable inputs through land management practices, training for labour and improved seeds can enable the farmers to take advantage of economies of scale. Chirwa (2007) study finds the returns to scale to be 0.97~1 which exhibits constant returns to scale whilst Anupama et al. (2005) find the returns to scale to be 0.5 as a result of decreasing returns to scale.

Variables	Elasticity
Seed/ha	0.25
Herbicide/ha	0.21
Labour/ha	0.02
Cost/ha	0.23
RTS	0.71

Source: Authors computation, 2012 All the input variables are significant at 1 percent with the exception of labour.

Table 4: Elasticity of production and returns to scale.

Variable	Parameters	Estimates	Standard Error
Constant	β_0	0.163***	0.055
Lnseed/ha	β_1	0.253**	0.110
Lnherbicide/ha	β_2	0.208***	0.053
Lnlabour/ha	β_3	0.021	0.066
Lnothercost/ha	β_4	0.230***	0.048
0.5Ln(seed)2	β_5	0.679**	0.300
0.5Ln(herbicide)2	β_6	0.149***	0.041
0.5Ln(labour)2	β_7	0.278**	0.166
0.5Ln(cost)2	β_8	-0.024	0.055
Lnseed*Lnherbicide	β_9	0.249***	0.087
Lnseed*Lnlabour	β_{10}	-0.432**	0.201
Lnseed*Lncost	β_{11}	-0.228**	0.104
Lnherbicide*Lnlabour	β_{12}	-0.040	0.076
Lnherbicide*Lncost	β_{13}	-0.033	0.036
Lnlabour*Lncost	β_{14}	0.001	0.074
Gamma	γ	0.80***	0.053
Loglikelihood value	λ	-0.89	

Note: **, *** corresponds with 5% and 1% levels of significance, respectively.
Source: Authors computation, 2012

Table 3: Maximum likelihood estimates of translog mean output function.

4. Technical Efficiency Estimates

Majority of the respondents represented by 48.3% produce at efficiency level ranging from 81% to 90% of their frontier output. But the technical efficiency estimates range from 24% to 96% at a mean of 83% and 3.1% of the producers attain technical efficiency levels below 50% of their respective frontier output. The findings implies that there is the possibility of increasing the output of maize farms in the study area by 17% on the average in the short run by adopting the practices of the best farm. In a related study of smallholder maize production in Southern Malawi, Chirwa (2007) finds the mean technical efficiency to be 46.23% between the range of 8.12% -93.95% (Table 5).

Estimates	Frequency	Percent
0.21-0.30	2	9
0.41-0.50	5	2.2
0.51-0.60	5	4.3
0.61-0.70	14	5.6
0.71-0.80	25	17.2
0.81-0.90	133	48.3
0.91-0.99	48	21.1
Minimum	24%	
Mean	83%	
Maximum	96%	
Total	**232**	**100.0**

Source: Authors computation, 2012

Table 5: Technical efficiency estimates.

5. Determinants of technical inefficiency

The results in Table 6 indicate that age-squared influence technical inefficiency because as age increases, technical inefficiency increases up to certain level but it decreases with further increase in age. Therefore the very old become efficient in the cultivation of maize due to their long experience to learn and adopt the best production practices on their farms. Villano & Fleming (2006) found that as farmers grow to gain experience it influences technical inefficiency negatively if the farmers gain experience to know the best farm practices and better perform them. Khan & Ali (2013) found younger farmers in Pakistan involved in tomato production to be more efficient. This is because the younger farmers tend to be more receptive to improved methods of tomato production to influence efficiency positively. Therefore farmers can grow to gain experience enough to become less risk averse to use improved production practices. Most producers of maize who use in-kind credit in the form of inputs such as seed and fertilizer revealed that the delivery of the inputs from suppliers was late to meet favorable weather conditions. As a result the applied inputs were not efficiently converted into maize output due to the late planting and this resulted to the positive influence of in-kind credit on technical inefficiency. Therefore access to in-kind credit does not guarantee gains in technical efficiency. Meanwhile in a related study of maize production in rural Vietnam, Duy (2012) finds both cash and in- kind credit to influence technical inefficiency negatively. Khan & Ali (2013) finds that farmers who lack access to credit are not able to realize their full production potential in tomato production due to their inability to invest in productive inputs like fertilizer, improved seeds and the use of other best agronomic practices. The finding suggest that if maize production depends on rainfall then the use of other risk mitigating strategies to control the effects of the weather vagaries are essential.

In relation to gender, Onumah et al. (2010), found males to be more efficient in fish farming than their female counterparts in Southern Ghana but this study finds that gender is unrelated to technical inefficiency. In their study males are more efficient in maize production due their ability to focus on maize production more than the females because the economic activity of maize production is their primary role in the household unlike females who together work as maize farmers as well as house wives. Again the males are able to perform the labor intensive farm practices in addition to the use of hired of labour. But females mainly rely on hired labour and with scarcity and unreliable nature of hired labour results to inadequacies in the performance of the best farm practices to impede their efficiency. The results of the study also reveal that maize producers level of education does not explain the variation in technical inefficiency. But Khan & Ali (2013) study reveals that if producers are educated it enhances the application of the best farm practices in tomato production process. Nyagaka et al. (2010) also observed a positive influence of education on technical efficiency in their studies. Binam et al. (2008) and Onumah et al. (2010) in their studies on the production of cocoa and fish respectively obtained mixed results about the role of education to the production of the frontier output. Studies in crop production such as Ogundari (2008) and Alhassan (2012) has found extension contact with the farmers to influence technical inefficiency

Variables	Parameters	Estimate	Standard Errors
Constant	δ_0	-1.44**	0.791
Age^2	δ_1	-0.002***	0.001
Credit	δ_2	1.759***	0.712
Gender	δ_3	-0.247	0.272
Edu	δ_4	-0.060	0.109
Numvisit	δ_5	-0.014	0.045
Dumplough	δ_6	2.600***	0.604
BKdistrict	δ_7	-0.089	0.271
Nkdistrict	δ_8	-3.905***	0.952
Kintampo	δ_9	-1.935***	0.571
Wencdist	δ_{10}	-1.058**	0.488

Note: **, *** corresponds with 5% and 1% levels of significance, respectively.
Source: Authors computation, 2012

Table 6. Maximum likelihood estimates of the technical inefficiency model.

negatively. But this study finds that extension contact does not explain technical inefficiency. Solís et al., (2006) study indicates that soil conservation practices result to higher levels of technical efficiency among farmers but the land management practice mostly used by the maize farmers such as ploughing of the land affects technical inefficiency positively. The study further demonstrates that Nkoranza, Kintampo, and Wenchi Districts influence technical inefficiency negatively with the exception of Sunyani West District. The producers of maize in these districts are less technically inefficient than their counterparts in the Sunyani West District. Therefore farmers in the Nkoranza, Kintampo and Wenchi Districts apply the best farm practices on their farms more efficiently than those in Sunyani (Table 6). A related study of cocoa production in Ghana by Dzene (2010) confirms the results of this study that district variation affects producers‘ ability to achieve the frontier output.

Conclusions

The study which analyzed technical efficiency of maize production in the Brong-Ahafo Region of Ghana revealed that the input factors (seed, herbicide, labour, land and cost of intermediate inputs) scaled per hectare- are productive at decreasing returns to scale. Cost of intermediate inputs and seed cause the most significant changes to maize output. Again the study indicates that on average, 17% of maize output in the Brong-Ahafo Region is lost due to technical inefficiency. Farmer location and characteristics such as age-squred contribute to the achievement of the frontier output. Also the timely application of in-kind credit facility which is supported by the application of risk mitigating techniques is essential to produce maize efficiently. Based on these findings, the study recommends that older farmers, especially those with less experience in maize production should be supported to adopt best farm practices on their farms. Farmers in the Sunyani west municipality should be trained to adopt best farm practices. Ploughing of the land should be carried out with green manuring to achieve the optimum results. The delays in the provision of in-kind credit should be minimized to meet favorable weather conditions for optimum use.

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