International Journal of Multidisciplinary Studies and Innovative Research
Publisher: Catholic University of Ghana
Editor-In-Chief: Prof. Daniel Obeng-Ofori

ISSN: 2737-7172 (O), ISSN: 2737-7180 (P)
Volume 10, Number 2, pp. 1531-1537
DOI: 10.53075/Ijmsirq/656357565465

Cassava: Farmers Adoption and Livelihood in Bono Region Performance of Stochastic Frontier Functions

Williams Awuma, [1] **Oke Samuel,** [2] **and Antwi-Adjei Alex** [3]

[1,2]Catholic University of Ghana, Fiapre, P.O. Box 363, Sunyani
[3]Ghana Communication Telecom University
Corresponding author email: koffiawuma@gail.com | Contact: 233(0)55 098 1438; +233(0)59 767 9347

Date received: August 16, 2022 **Date published:** October 5, 2022

Abstract: The objective is to analyze the stochastic frontier function in comparing the performance of the Cobb-Douglas and Translog Frontier functions in the cultivation of cassava in the Bono Region of Ghana. The assumption is that given the same level of productive inputs of farmers at any given farming season, across heterogenous farm lands, both functions are likely to produce the same results. Interview was used as the instrument for obtaining plot-specific data from 120 cassava farmers across six districts and data was analyzed using quantitative technique. Direct predictors of output include plot size, labour, hoes, cutlasses and cassava stems. Using half-normal distributional assumption, the study evaluates variance parameters of the composed error terms. The results showed that the estimated functions produced comparable results in terms of magnitude and signs of input variables. While efficiency appeared to be much higher in Cobb-Douglas than the Translog function, the variance parameter score for CD function is significantly different from those of Translog function and the maximum output attainable for the given productive inputs were 40% and 15% respectively. The means that farmers can scale up their current crop yield by 60% and 85% respectively of their frontier functions using the same inputs and technology, if the appropriate interventions are carried out. The limitation of the study is non-inclusion of environmental factors such as rain as productive input and the study is limited to comparing frontier functions. The results underscored the importance of examining the current production behaviour of farmers for reliability and policy inferences

Keywords: Stochastic frontier function, cobb-douglas, translog, cross-sectional data, cassava

1. INTRODUCTION

Planting for Food and Jobs (PFJ) was launched in 2017 under Planting for Export and Rural Development and Rearing for Food and Jobs. Subsequently, three other modules were designed including Mechanization, Greenhouse Villages and the Food module which were designed in order to facilitate the transformation of agricultural sector in Ghana. According, Ghana Statistical Service (GSS, 2018) after three years of its implementation, the agricultural sector witnessed a GDP growth rate of about 6.1 percent in in 2017 and 4.8 percent in 2018. In the second year PFJ recorded 1,510,330 metric ton in food production with a value of input support at GHS365,965,367 which accounted for value of food produced at GHS3,426,983,000 equivalent to USD616,363,849. On the account of the success of the programme in 2017, expanded version was launched in 2018 targeting 500,000 farmers for assistance and at the end of that year about 577,000 farmers had accessed inputs, far in excess of the planned target for the year. 1n 2019, the programme had enrolled about 1,183,313 farmers out of the projected 1.2 million farmers. In 2018, a total of 183,000 metric tons of fertilizer, 7,600 metric tons of seeds and cassava planting materials were distributed across the country. In 2019. 13,000 metric tons of subsidized seeds for "priority crops" including cereals, legumes and vegetables and 200,000 bundles of cassava planting material, 438,900 metric ton of subsidized inorganic fertilizer and 30,000 metric tons of organic fertilizer were distributed. In the Bono Region in particular, the programme has benefited 428,000 farmers including 252,691 males and 175,504 females, cultivating a total of 72,011 hectares in 2019 and 73,783 hectares in 2020 by producing 1,679,893 and 1,731,383 metric tons respectively. Given the various interventions and policies implemented over the years to raise farmers productivity and efficiency under the Planting for Food and Jobs (PF&J) in Ghana, it is envisaged that effective cassava production policy can push forth Ghana food and derivatives production, but empirical literature suggests that efficient cassava production hinges on application of the appropriate production function. Although there has been improvement in cassava production, the production technique remained largely unknown. Such an empirical analysis will guide government in improving the welfare of farmers under the programme if further policy intervention warrants that cassava production be expanded. Understanding the production techniques of farmers will provide an important input to agricultural policy choices in the region. The objective of the study is to investigate the performance of the production techniques of farmers using the stochastic frontier function in Cobb-Douglas and Translog function which evaluate the variance parameters of the composed error terms. An important feature of the frontier model is its ability to allow the composite error to assume three distributional specifications.

2. MATERIALS AND METHODS

Study Area

Bono Region shares a border at the north with the Savannah Region, is bordered on the west by Ghana-Côte d'Ivoire international border, on the east by Bono East, and on the south by Ahafo Region. The region has a population of about 1,208,649 comprising urban and rural population distribution of 708,481 and 500,168 respectively according to Ghana Statistical Service (2021). The region's topography can be described as a low elevation not exceeding 152 metres above sea level. It has moist semi-deciduous forest and the soil type is very fertile. Agriculture in the region is heavily influenced by two major rainy seasons. The major season starts from March/April and ends in August, while the minor seasons starts from September and ends in December. The farmers in the region practiced slash and burn agriculture and use of agrochemical in farming. The region produces cash crops like cashew, timber, etc., and food crops such as maize, cassava, plantain, cocoyam, tomatoes, and many others

Sampling Procedures

A three-stage sampling technique was adopted in selecting cassava farmers for the study. Six districts were purposively chosen out of the twelve (12) districts based on location where cassava is widely grown all year round. At the second stage, a random sampling of two (2) cassava producing rural communities from each of the six (6) district was conducted, this was followed by randomly selecting twenty (20) cassava farmers from each rural community, thus making a total sample size of hundred and twenty (120) farmers. Data gathering was mainly interviews on cassava output and production inputs such as plot size, land, labour, hoes, cutlasses and cassava stems.

Analytical Framework

All production processes represent a transformation of inputs (for example, labour, capital, and raw materials) into outputs (which can be either in physical units or service). For this study, the production technology of cassava cultivation is assumed to be specified by the equation

$$Iny_i = \beta_i Inx_i + \epsilon_i$$

where y_i represents the quantity of output produced, x_i represents the number of inputs employed to produce a single output y_i, including L, the total landholding (acres), M, the quantity of manual labourers employed, H, the quantity of hoes used (units), C, the quantity of cutlasses (units) and S, approximated quantity of cassava stems planted and ϵ_i is the disturbance term. Given the above specification, a number of assumptions were made: that cassava farmers have employed the same production technology to achieve maximum output given identical set of inputs in a heterogeneous production environment, and with identical inputs, farmers produced different outputs with different technical efficiency The efficiency differences may be attributed to differences in environmental factors (such as weather, land topography, and soil types) and institutional factors (like access to credit and extension services, and managerial factors like the age, skills, aptitudes, and gender of farm operators) as argued by Ali et al (2022).

Stochastic Frontier Model

The stochastic frontier model assumed the presence of technical inefficiency in production and by following Aigner et al. (1977) and Meeusen and van den Broeck (1977), the frontier function can be specified as

$$LnY_i = f[(x_i, \beta)]exp(v_i - u_i)$$

Such that LnY_i is the logarithm of output maximum output produced, x_i is $[k \times 1]$ vector of logarithm of quantities of productive inputs, β is $[k \times 1]$ vector of unknown parameters. The stochastic frontier function is such that technical efficiency is defined as a ratio of observed output to corresponding frontier output conditional on input, such that the frontier output is specified as

$$LnY_i = f[(x_i, \beta)]exp(v_i)$$

The assumption of the above model is that it contains no inefficiency and hence the exclusion of (u_i). The technical inefficiency according Aigner et al. (1977) and Meeusen and Van den Broeck (1977) can then be specified as

$$TE_i = \frac{f[(x_i, \beta)]exp(v_i - u_i)}{f[(x_i, \beta)]exp(v_i)} = exp(-u_i)$$

where $[(0 \leq TE_i \leq 1)]$. When $[(TE_i = 1)]$ production is said to technically efficient, that production being on the frontier and when $[(TE_i < 1)]$ production is technically inefficient (Battese and Coelli,1992; Kumbhakar, 1990)

Variance Parameters

In the stochastic frontier model, the composed error terms are expressed as $(v_i - u_i)$ where v_i is the stochastic error distributed as $N[(0, \sigma_v^2)]$ and u_i is the one-sided error distributed as $N[0, \sigma_u^2]$, which are distributed independently of each other. The variance parameters of v_i and u_i are σ_v^2 and σ_u^2 respectively. The sum of the two variances, sigma-square $\sigma^2 = [\sigma_v^2 + \sigma_u^2]$ and gamma $\gamma = [\sigma_u^2/(\sigma_v^2 + \sigma_u^2)]$ provide information on the distributional appropriateness of using a stochastic specification and the distributional form of the two-part terms (Coelli, 1995; Battese et al., 2004). The value of gamma indicates the proportion of variation in the model that may be due to capacity utilization. In the estimation of these functional forms with parametric distributional assumption, Agner et al, (1977) adopted a half-normal, truncated-normal and the exponential distributional assumption for u_i.This means that the functions can be estimated using distributions. The half-normal distribution is described as a special case of the truncated normal distribution which involved the restriction $H_0: \mu = 0$. As proposed by Battesse and Coelli (1992) in agricultural literature, the basic half-normal model can be specified as

$$Iny_i = \alpha + Inf(x_i; \beta) + (v_i - u_i)$$

$$v_i \sim N(0, \sigma_v^2)$$
$$u_i = exp\left[\left(-\eta(t - T_i)\right)\right], u_i \sim N^+(0, \sigma_u^2)$$
$$\epsilon_i = v_i - u_i$$

where Iny_i represents the logarithm of output (cassava) i, x_i is a matrix of logarithm of productive inputs, v_i is a random error normally distributed with zero mean and variance σ_u^2, u_i is a non-negative inefficiency term which changes over time exponentially with additional parameter η and t indicates current production period, T_i is the terminal period. ϵ_i is the composed error term, α is a common intercept for all the inputs and β are the technical parameters to be estimated. The above equation allows the u_i to be distributed truncated-normal as $u_i \sim N^+(0, \sigma_u^2)$.

Empirical Model Specification

The Cobb-Douglas (CD) stochastic production frontier function

The Cobb-Douglas form of the stochastic frontier production function applied in this study is specified

$$Iny = \beta_0 + \sum \beta_j Inx_j + (v_i - u_i)$$

where In is the natural logarithm of output and the respective inputs x_j(using five inputs of production such as Land, Manhour, Hoes, Cutlasses and Stems), β_j are input parameters to be estimated. This functional form imposes more stringent assumption on the data because of the elasticity of substitution has a constant value of one and the elasticity of production is constant for all inputs

Translog stochastic production frontier function

The Translog form of the stochastic frontier production function (Christensen, Jorgenson, and Lau., 1971) applied in this study is given as:

$$Iny = \beta_0 + \sum \beta_j Inx_j + \frac{1}{2}\sum_j \sum_k \beta_{jk} Inx_j Inx_k + (v_i - u_i)$$

The alternative function approximates the logarithmic of output by a quadratic in the logarithmic of the productive input and also involves the estimation of the parameters of inputs and interactive inputs as captured in the CD function.

3. RESULTS AND DISCUSSION

The estimated coefficients of input variables used in both Cobb-Douglas and Translog production frontier functions are presented in Table 1.

Table 1: Estimated Production Functions

$Inputs$	$Model\ 1[OLS]$ CD	$Model\ 2[OLS]$ $Translog$	$Model\ 3[ML]$ CD	$Model\ 4[ML]$ $Translog$
$LogL$	0.3349^{**}	0.7518	0.3159^{**}	0.1188
	(0.0886)	(0.8929)	(0.0805)	(0.2314)
$LogM$	0.1828^{**}	0.7397	0.1895^{*}	0.1179
	(0.1132)	(1.3050)	(0.1094)	(0.8881)
$LogH$	0.2361^{**}	-0.5332	0.2591^{**}	0.5858
	(0.0776)	(1.1429)	(0.0769)	(0.4882)
$LogC$	-0.03161	0.2341	-0.0111	-0.2188
	(0.0543)	(0.8984)	(0.0616)	(0.5348)
$LogS$	0.5758^{**}	1.5082	0.5217^{**}	0.5168^{**}
	(0.1511)	(1.8941)	(0.1126)	(0.1776)
R^2	0.7419	0.9852		
$\bar{R}^2$	0.7306	0.9853		

$(LogL)(LogL)$	0.0553	−0.0071
	(0.0299)	(0.0193)
$(LogM)(LogM)$	−0.0900	−0.0118
	(0.0735)	(0.0242)
$(LogH)(LogH)$	0.0321	0.0259
	(0.0434)	(0.0226)
$(LogC)(LogC)$	0.0034	−0.0106
	(0.0202)	(0.0112)
$(LogS)(LogS)$	−0.0956	−0.0212
	(0.1156)	(0.0224)
$(LogL)(LogM)$	−0.0220	−0.0319
	(0.1415)	(0.1109)
$(LogL)(LogH$	−0.2285	−0.0138
	(0.1010)	(0.0659)
$(LogL)(LogC)$	0.0620	−0.0495
	(0.1278)	(0.1278)
$(LogL)(LogS)$	−0.0388	0.0015
	(0.1171)	(0.0342)
$(LogM)(LogH)$	−0.0128	−0.0080
	(0.0700)	(0.0242)
$(LogM)(LogC)$	−0.0352	0.0269
	(0.0668)	(0.0159)
$(LogM)(LogS)$	−0.0391	−0.0121
	(0.1605)	(0.1100)
$(LogH)(LogC)$	−0.0089	−0.0013
	(0.4056)	(0.0254)
$(LogH)(LogS)$	0.0481	−0.0819
	(0.1366)	(0.0632)
$(LogC)(LogS)$	−0.0212	0.0213
	(0.1069)	(0.0664)

Source: Field Data, 2022
$**$ Statistical significance at 5% level

CD Function

The OLS estimates of the frontier models are presented in columns 1 and 2 respectively in Table 1. In the CD function, the OLS coefficients of $LogL$, $LogM$, $LogH$, $LogC$ and $LogS$ are consistent for the production frontier model as they align with expectations and found to be statistically significant except $LogC$. The estimate for $LogC$ is -0.0316 with $p\ value$ equal to 0.561, this may imply that the inclusion of this variable in model is not supported by data. The standard errors of the estimated coefficients are in parentheses. The five inputs showed a production technology close to increasing returns to scale (i.e., the sum of the coefficients: $[0.3349 + 0.1828 + 0.2361 + 0.5758 - 0.0316]$. This implied that any increase in plot size and capital inputs such as hoes and stems would increase output considerably as this was expected and in accordance with a priori expectations. The estimated coefficients on the frontier function in column 3 are close to the OLS estimates as shown on Table 1, this is because of the consistency of the OLS estimates. The iteration log for the frontier function showed that the estimation converged at the fourth iterations for CD function with loglikelihood value of 64.020412

Translog Function

The OLS and frontier estimates presented in columns 2 and 4 respectively revealed that many of the input variables are not significant at the 5% level except for cassava stems as shown in model 2, this is due largely to square terms and interactive effects of the input variable (Lira et al, 2014; Wang, 2002). Again, the coefficients of the frontier function in model 4 are very similar to those of OLS model 2. The elasticity estimates showed that cassava farmers are operating at an increasing return to scale, as the sum of the estimated coefficients was greater one. The loglikelihood value of model 4 is 155.17423 which is higher than model 3 loglikelihood value of 64.020412. This information is in turn useful in comparing the performance of both models. Allowing for half-normal model with exogenous determinants of output, we estimated the variance parameters in both models

Table 2: Estimated Variance Parameters

	$Parameters$	$Coeff$	$Std\ Err$	t	$P > [t]$
	σ_v^2	-2.3262	0.3416	-6.8079	0.000
	σ_u^2	-1.5839	0.4896	-3.2351	0.001
CD Function	σ_v	0.3125	0.0533	5.8630	
	σ_u	0.4530	0.1169	3.8751	
	σ^2	0.3028	0.0770	3.9325	
	$Lambda(\lambda)$	1.4494	0.1564	9.2673	
	$Gamma(\gamma)$	0.4051			
	σ_v^2	-22.4755	13.0352	-1.7242	0.085
	σ_u^2	-4.0378	0.1291	-31.2741	0.000
	σ_v	0.0000123	0.0000858	0.1434	
Translog	σ_u	0.1328	0.0086	15.4418	
	σ^2	0.0176	0.0023	7.6523	
	$Lambda(\lambda)$	10085.08	0.0086	1,172,684	
	$Gamma(\gamma)$	0.1523			

Source: Field Data, 2022

Using the composed error terms of the stochastic frontier models, the total variation in output from the frontier level of output attributed to technical efficiency is defined by $\gamma = [\sigma_u^2/(\sigma_v^2 + \sigma_u^2)]$. The variance parameter γ lied on the interval [0,1] as obtained. And using the half-normal distributional assumption by (Kalirajan and Flinn, 1983; Dawson and Lingard, 1989; Battese and Coelli,1995), the ratio of output specific variability to total variability, γ is positive and significant, implying that cassava production specific technical efficiency is important in explaining the total variability of output produced, this is confirmed by the significance of the variances of the one-sided error, $[\sigma_u^2]$ in both models at 5% level. This implied that $H_0: \mu = 0$ is rejected in both models – an indicative that all deviations from the frontier are due to inefficient effect. Again, the variance parameters in both models recorded their negative values, this is because the unconstrained numerical maximization would not guarantee positive estimates as suggested by (Kumbhakar et al., 2010). Given the input bundles, the maximum output attainable is indicated by the γ estimates. Following the LR test for model specification, the hypothesis that the CD function offer adequate representation of the data is accepted, that is, the nature of the gaps between the observed production and the maximum production has been explained adequately by the CD function and hence provided preferred formulation in comparison to the Translog function.

4. CONCLUSION

In this paper, we estimated the stochastic frontier production function in both CD and Translog production functions. The results revealed that the maximum output attainable for given inputs in both functions were 40% and 15% respectively according to half-normal distributional assumption. This implied that, we observed greater technical inefficiencies for different plots sizes in case of the half-normal distribution, that is farmers operate 40% and 15% respectively below their potential frontier function level with the given inputs and production technology. These values indicated that farmers can improve their current output levels by 60% and 85% respectively by the same set of inputs and technology. These results call for policy intervention by government aimed at encouraging the use of the CD production function based on its estimated coefficients and the values of the variance parameters, thus technical efficiency can be improved if farmers can adjust their input quantities.

5. ACKNOWLEDGEMENT

We are thankful to the International Journal of Multidisciplinary Studies and Innovative Research's reviewer board for their constructive comments and recommendations, which have improved the quality of this research article.

6. REFERENCES

Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977), "Formulation and Estimation of Stochastic Frontier Production Function Models" *Journal of Econometrics*, 6, 21–37.

Ajibefun, I. A., & Aderinola, E. A. (2004). Determinants of technical efficiency and policy implication in traditional agricultural production: *Empirical study of Nigerian food crop farmers*. Final Report Presentation at Bi-annual Research Workshop of African Economic Research Consortium, Nairobi, Kenya.

Ajibefun, I. A., & Daramola, A. G. (2003), "Efficiency of Micro Enterprises in the Nigerian Economy. AERC Research paper 134. *African Economic Research Consortium*, Nairobi, 7, 1-42.

Ali, M., & Chaudhry, M. A. (1990), "Inter-regional Farm Efficiency in Pakistan's Punjab: A Frontier Production Function Study," *Journal of Agricultural Economics*, 41, 62–74.

Battese, G. E., & Coelli, T. J. (1995), "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data," *Empirical Economics*, 20, 325–32

Battese, G. E., & Coelli, T. J. (1992), "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India," *Journal of Productivity Analysis*, 3, 153–69

Battese, G. E., Rao, D.S.P., and O'Donnell, C.J. (2004), "A Metafrontier Production Frontier for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating under Different Technologies," *Journal of Productivity Analysis,* 21, 91-103

Christensen, L.R., Jorgenson, D.W., and Lau, L.J. (1971)," Conjugate Duality and Transcendental Logarithmic Function" *Econometrica*, 39, 255-6

Coelli, T. J., Rao, D. S. P., & Battese, G. (1998), "An Introduction to Efficiency and Productivity Analysis," Boston, MA: Kluwer Academic Press

Coelli, T.J. (1995), "Estimators and Hypothesis Test for a Stochastic Frontier Functions: A Monte-Carlo Analysis," *Journal of Productivity Analysis,* 6, 247-68

Dawson, P. and Lingard, J. (1989), "Measuring Farm Efficiency over time on Philippine Rice Farms", *Journal of Agricultural Economics*, 40, 168-77.

GSS (2018), "Gross Domestic Product 2018," Accra: Ghana Statistical Service.

GSS (2021), "Gross Domestic Product 2021," Accra: Ghana Statistical Service.

Kalirajan, K. P. and Flinn, J, C. (1983), "Comparative Technical Inefficiency in Rice Production", *Philippines Economic Journal*, 20, 31-34.

Kumbhakar, S.C (1990), "Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency," *Journal of Econometrics*, 46, 201–11.

Kumbhakar, S.C., Wang, H.J., and Horncastle, A. (2010), "Estimation of Technical Inefficiency in Production Frontier Models Using Cross-Sectional Data," Indian Economic Review, 45, 7-77

Lira, M., Shamsudin, M.N., Radam, A. and Mohamed Z. (2014), "Efficiency of Rice Farms and Its Determinant: Application of Stochastic Frontier Analysis," *Trends in Applied Science Research*, 9, 360-371

Meeusen, N., and van den Broeck, J. (1977), "Efficiency Estimation from Cobb Douglas Production Function with Composite Error," *International Economic Review*, 18, 435–44.

Wang, H.J. (2002), "Heteroscedasticity and Non-Monotonic Efficiency Effects of a Stochastic Frontier Model," *Journal of Productivity Analysis,* 18, 241-53

Wang, H.J., Amsler, C., and Schmidt, P. (2011), "Goodness of Fit Tests in Stochastic Frontier Models," *Journal of Productivity Analysis,* 35, 95-118