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Application of Stochastic Frontier Production Function to Separate the Effect of Random Variation in Output from Inefficiency in the Agricultural Production of African Countries

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Abstract
The paper applied the stochastic frontier production function to separate the effect of random variation in output from inefficiency in the agricultural production of African countries. The general Cobb-Douglas and translog functional forms were tested for adequate functional form. A Quasi-translog production frontier function was specified using a balanced panel data of 26 African countries, drawn from Food and Agriculture Organization covering the period 1961-2009. The parameters in the Quasi translog stochastic frontier production function were estimated by the maximum-likelihood method using FRONTIER 4.1. The stochastic frontier incorporates stochastic output variability by means of a two-part error term. In order to separate deviations away from the frontier production function into random variation and inefficiency, a distribution assumption for both parts of the error term was imposed and the error term of the stochastic frontier calculated. The test result suggests that the random term has a truncated normal distribution. Out of the five input variables used, land, labour and livestock significantly influence the agricultural production of the panel of African countries. Furthermore, the agricultural production function operated at a technical regress in a panel of African countries, implying that there is a possibility to increase production by improving the use of input resource. It was observed that 92.4% of the variation in output was due to technical inefficiency. While 7.6 % of the variation in output is explained by the stochastic random variation, implying that the agricultural industry stochastic random error is important in explaining the total variability of agricultural output produced. This was not unexpected in the African agricultural production where random shocks or measurement error are assumed to be vital sources of variation in output.
Keywords: Random variation, Inefficiency, stochastic frontier production function, maximum-likelihood method, Agricultural production

Introduction

The measurement of production performance has remained an area of important research, especially in developing countries, where resources are scanty and opportunities for developing by inventing or adopting better technologies are dwindling (Ogundari, 2014). A common approach has been to estimate a production frontier, which represents the relationship between the maximum potential output for a given set of inputs. The individual's output is compared to the frontier level of output given the level of inputs employed, and the resultant difference represents the level of inefficiency of the country (Pascoe et.al, 2001). A technically efficient country is said to operate on the production frontier, but a technically inefficient country's operation is located beneath the production frontier. This however, ignores the possibility that a country's performance may be affected by factors entirely outside its control. A country may deviate from the production frontier not only due to technical inefficiency but also from measurement errors; statistical noise or other non-systematic influences (Pascoe and Coglan, 2000). As noted by Wadud and White (2000), agricultural production is a biological process heavily affected by weather, pest, diseases, etc. which can be a deterrent or motivation for farmers to use more inputs in production. In addition, agricultural production in most African countries is characterised by smallholder type production which often involves whole families as working units, as such the keeping of accurate records is not always a priority. Thus, more available data on production are likely to be subject to measurement errors and they can have a large influence upon the shape and positioning of the estimated frontier (Admassie and Matambalya, 2002). Under these circumstances it is essential to distinguish between the role random disturbances play in determining the magnitude of production and the impacts of inefficiency on deviation from the production frontier. Jerzmanowski (2007), has observed that deviations of actual output level from the production possibility frontier appears to be the main explanation for low incomes in the world.

Previous studies (Wouterse, 2010, Omondi, and Kelvin, 2013, Adama, 2014), measuring technical inefficiencies have specified a non-stochastic or deterministic frontier model of Cobb Douglas production function. According to (Kumbhaker and Lovell, 2000), this model does not take account the possible influences of measurement errors and other noises up on the shape and positioning of the estimated frontier. Alternatively, any deviation from the frontier will be taken as inefficiency. Application of this model, especially in cases where there is high probability of measurement risk, will exaggerate the inefficiency estimates as compared to the models which decompose the error term into two components, e.g. the stochastic frontier production function approach. The stochastic frontier approach allows for random disturbances, such as weather conditions, the effects of pest and diseases, and measurement errors in the output variables (Kumbhaker, 2001). A number of studies estimating the stochastic frontier have mainly been implemented with cross-sectional data and not within the context of panel data and had tended to explicitly model inefficiency as a function of country-specific explanatory variables (Burhan et al 2009). The major objective of these studies was to examine the effects of particular factors on the efficiency of production, without paying attention to random disturbances. However, random disturbances can have broad-reaching impacts on production output (Omondi and Kelvin (2013).

The main objective of this paper was to apply the stochastic frontier production function to separate the effect of random variation in output from inefficiency in the agricultural production of African countries, using panel data which offers a more efficient econometric estimation of the production frontier model (Breitung, 2000). The stochastic frontier is based on the idea that an economic unit may operate below its production frontier due to errors and some uncontrollable factors. This was pursued by testing the general Cobb-Douglas and translog functional forms for adequate functional form. A Quasi-translog production frontier function was specified using a balanced panel data of 26 African countries, covering the period 1961-2009. The stochastic frontier incorporates stochastic output variability by means of a two-part error term. The parameters in the Quasi-translog stochastic frontier production function were estimated by the maximum-likelihood method using FRONTIER 4.1. In order to separate deviations away from the frontier production function into random variation and inefficiency, a distribution assumption for both parts of the error term was imposed and the error term of the stochastic frontier calculated. As suggested by Omondi and Kelvin (2013), the composed error of the stochastic frontier production function causes the deviation from the frontier. Information about deviation resulting from random disturbances as distinct from inefficiency is important in policymaking for promoting efficiency in the production of scarce resources. In addition, the use of panel data, repeated observations on each production unit, generates information not provided by simply adding more producers to a cross-section data set (Burhan et.al 2009). By providing such information, a substantial contribution would have been made towards the need to reduce inefficiency and improve efficiency or to develop new technology to raise agricultural production by policy makers. The specific objectives of the paper were two-fold: (i) to estimate the influence of input variables on the amount of output in the agricultural production of African countries (ii) to investigate whether variation in output are explained by random disturbances in the agricultural production of African countries. To guide research, the following null hypotheses were stated (i) employed input variables do not influence the amount of output in the agricultural production of African countries (ii) variation in output is not explained by random disturbances in the agricultural production of African countries. The rest of the paper is organized as follows. The next section highlights the material and methods used for the study. This is followed by the section that presents the data and variables. The results and discussion section followed. The last section concludes.

Materials and Methods

This study employs stochastic frontier production function which requires a parametric representation of the production technology. In addition, it incorporates stochastic output variability by means of a two-part error term. The distributional assumptions for both parts of the error term are imposed. Kumbhaker and Lovell (2000) specified a panel data version of the stochastic frontier production function of the form:

$$Y_{it} = x_{it}\beta + \varepsilon_{it} \text{ .... } (1)$$

where, y_{it} is the output of the production unit i (i=1, 2, …, N) at time t (t=1, 2, …,T),

x_{it} is the matrix of j inputs, t is a time index that serves as a proxy for technical change,

β are the parameters to be estimated and ε_{it} is the composed error term. Following Pascoe and Coglan (2000), ε_{it} is defined as:

$$\varepsilon_{it} = v_{it} - u_{it} \text{ .... } (2)$$

The symmetric component v_{it}, is identically and independently distributed and captures random variation in output resulting from factors outside the control of the producer (weather, diseases, machine breakdown, etc.) as well as measurement errors and left-out explanatory variables. The one-sided component $u_{it} > 0$ reflects technical inefficiency relative to the stochastic frontier of the i^{th} country at year t.

Bravo-Uretta (2007) proposed the Log Likelihood (LL) function for the model in equation (2) assuming half normal distribution for the technical inefficiency effects (u_{it}). They expressed the likelihood function using γ parameterization, where, $\gamma = \dfrac{\sigma^2_{u_{it}}}{\sigma^2_{v_{it}} + \sigma^2_{u_{it}}}$

They specified the log likelihood function of the model as:

$$In(L) = -\frac{N}{2}\left(In\left(\frac{\pi}{2}\right) + In\sigma^2\right) + \sum_{i=1}^{N} In\left[1 - \Phi\left(\frac{\varepsilon_i\sqrt{\gamma}}{\sigma^2}\sqrt{\frac{\gamma}{1-\gamma}}\right) - \frac{1}{2\sigma^2}\sum \varepsilon_i^2\right] \text{ .... } (3)$$

Where $\varepsilon_i = In \times_i \beta - \alpha_k hZ_{ik}$ is the residual of equation (1)

N is the number of observations

$\Phi(.)$ is the standard normal distribution $\sigma^2 = \sigma^2_{v_{it}} + \sigma^2_{u_{it}}$ and $\gamma = \sigma^2_{u_{it}} \big/ \sigma^2$ are variance parameters.

The minimization of (3) with respect to β, σ^2, α, and solving the resulting partial derivatives simultaneously, produces the maximum likelihood (ML) estimates of $\beta, \sigma^2, and \alpha$. The γ parameter can be interpreted as the percentage of the variation in output that is due to technical inefficiency. Likewise the σ^2 parameter is interpreted as the variation in output explained by the stochastic random variation.

Data and Variables

The specification of a production function requires the definition of only two types of variables: the output of agricultural production and the inputs employed in the production process. Panel data used for this study were drawn from the Food and Agricultural Organization Statistics (FAOSTAT) of the United Nations for the period 1961-2009 on twenty-six African countries. They include- Algeria Egypt, Libya, Morocco, Tunisia, Burkina-Faso, Gambia, Niger, Senegal, Sudan, Burundi, Kenya, Tanzania, Uganda, Benin, Cote d'Ivoire, Ghana, Guinea, Nigeria, Togo, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe. The output measure (y_{it}) is expressed as the quantity of agricultural production in millions of 1999-2001"international dollars". Procedurally, the measure calculates weighted world prices for each commodity, and then multiplies each country's commodity quantities by the weighted world prices. To avoid double counting of output, the feed output used as an input for livestock is subtracted from total agricultural output. Inputs employed in agricultural production are represented in this study by five variables: Land area (A_{it}) measured as the sum of arable land, permanent crops and permanent pastures, in 1,000 hectares. Total labour (L_{it}) measured as the number of persons who are economically actively engaged in agriculture, in thousands. Tractor (Tr_{it}) the total number of agricultural tractors in use, Fertilizer (F_{it}) quantity of fertilizer plant nutrient consumed (N plus P2O5 plus K2O), in metric tons, Livestock (S_{it}) a weighted average of the number of animals on farms (weights are: camels 1.1; buffalo, horses and mules 1.0; cattle and asses 0.8; sheep and goats 0.1; pigs 0.2; fowl 0.01), in 1,000's. These input variables represent conventional inputs used for efficient agricultural production in developing countries.

Table 1: Summary Statistics of Data Sample

Variable	Minimum	Maximum	Mean	Std. Dev.
In (output)	4.769	7.453	6.096	0.504
In (land)	2.083	4.597	3.570	0.454
In (labour)	1.964	4.253	3.393	0.479
In (tractor)	0.301	5.244	3.453	1.040
In (fertilizer)	1.322	6.262	4.197	1.074
In (livestock)	4.888	7.463	6.145	0.510

Source: Own Estimates

Model Specifications

The use of the stochastic frontier requires that the functional form of the production function and the distributional assumptions of the two error terms be explicitly specified. The estimation of the stochastic frontier requires that the functional form of the production function and the distributional assumptions of the two error terms be explicitly specified. The general Cobb-Douglas and translog functional forms were tested for adequate functional form. The Cobb-Douglas and translog functional forms can be written as:

$$Iny_{it} = \beta_0 + \sum_{k=1}^{5} \beta_k Inx_{kit} + v_{it} - u_{it} \text{ .... } 4$$

and

$$Iny_{it} = \beta_0 + \sum_{k=1}^{5} \beta_k Inx_{kit} + \sum_{k=1}^{5}\sum_{j=1}^{5} \beta_{kj} Inx_{kit} Inx_{jit} + v_{it} - u_{it} \text{ .... } 5$$

respectively. Where, i represents a country, t represents the year of observation (1961 =1)

Y_{it} denotes the gross output at constant prices (million US $) in the i[th] country in year t and x_{kit} = (A_{it} , L_{it}, T_{rit}, F_{it} , S_{it}) denote the land area (1,000 hectares), the total labour used (in thousands) , the total agricultural tractors in use (numbers) the total quantity of fertilizer used(metric tons) and the total livestock (in 1000's) respectively. The inclusion of time as a variable allows for the shift of the frontier over time, which is interpreted as technical change. Since only ε_{it} is observed, distributional assumptions for v_{it} and u_{it} must be made. In most applications it is assumed that v_{it} follows a normal and u_{it} a half-normal distribution, and that $\text{cov}(v_{it}, u_{it})$= 0. Although a range of distributional assumptions have been proposed, there are no a priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Bravo-Uretta, 2007).

Hypothesis Tests

Four null hypothesis tests were conducted as follows: (i) the general Cobb-Douglas (CD) functional form is an adequate representation of the data, (ii) the absence of technical change in the African agricultural production, (iii) the systematic and random technical variations are zero (iv) the inefficiencies are time-invariant, (v) the half-normal distribution is an adequate representation for the distribution of the inefficiency (see Table 1). A likelihood-ratio test (LR test) was used to test these hypotheses, which can be conducted as follows:

$$\lambda = -2\{\log[L(H_0)] - \log[L(H_1)]\} \text{ .... (6)}$$

Where, $\log[L(H_0)]$and $\log[L(H_1)]$ are obtained from the maximized values of the log-likelihood function under the null hypothesis (H_0) and the alternative hypothesis (H_1) respectively. The LR test statistic has an asymptotic chi-square distribution with parameters equal to the number of restricted parameters imposed under the null hypothesis. The estimates of equations (3) and (4) show that the null hypothesis $H_0 : \beta_{ij} = 0$ could not be rejected; which indicates that the underlying stochastic production frontier function is best specified by a production function in generalized Cobb-Douglas form model. The function may be referred as Quasi-translog which can also be viewed as a translog specification without cross terms, i.e. a strongly separable-inputs translog production frontier function (Fan 1991). This production function can be specified as:

$$Iny_{it} = \beta_0 + \sum_{k=1}^{5} \beta_k Inx_{kit} + v_{it} - u_{it} \text{ .... (7)}$$

Rewriting the production frontier, the output function can be written as:

$$\begin{aligned} InY_{it} &= \alpha_0 + \alpha_h InH_{it} + \alpha_l InL_{it} + \alpha_k InK_{it} + \alpha_f InF_{it} + \alpha_s InS_{it} + \alpha 0.5tt + \alpha_{ht}(InH_{it}) \\ &+ \alpha_l (InL_{it}) + \alpha_k (InK_{it}) + \alpha_f (InF_{it}) + \alpha_s (InS_{it}) + (v_{it} - u_{it}) \text{..................................(8)} \end{aligned}$$

where, Y_{it} = the gross output at constant prices (million US $) in the i[th] zone in year t, A_{it} = hectares of the land area, L_{it} = the total labour used (persons), K_{it} = the total agricultural tractors in use (numbers), F_{it} = the total quantity of fertilizer used(tons), S_{it} = the total livestock (numbers) respectively, $\alpha's$ = parameters to be estimated, vit = a random variation with normal properties as explained above, μ_{it}= country inefficiency distribution term. A likelihood-ratio test (LR test) was used to test these hypotheses, which can be conducted following equation (6). Table 2 presents the results of the LR tests. Test (i) shows that given the specification of the stochastic frontier model, the null hypothesis that the general Cobb-Douglas (CD) functional form is an adequate representation of the data could not be rejected at the 5 per cent level. The values of the logarithm of the likelihood function for the generalised Cobb Douglas and full Translog Frontier Model were 12.285 and 21.952, respectively. As a result, the generalized likelihood ratio test statistics came out to be 19.334, which is less than the critical chi square table value of 24.384 at 15 degree of freedom (the difference between the numbers of parameters of the two models. This suggests that the generalized CD function (Quasi-translog) is an adequate representation of the data. The results and discussion of this paper were based on the Quasi-translog form. In the second test (ii), the null hypothesis that there is no technical change in the African agricultural production was considered. This was to test whether the time variable should be included in the model. If the LR test value is greater than the critical value, the null hypothesis of no technical change is rejected. Test result suggests that LR test value of 3.48 is greater than critical value 2.71. Hence, the time variable was included in the model. The null hypothesis (iii) considers the null hypothesis that the inefficiencies are time-invariant. The result show that the test value of 200.70 is greater than the critical value of 2.71. Therefore the null hypothesis was rejected, suggesting that the inefficiencies are time-varying. In test (iv), the null hypothesis that the half-normal distribution is an adequate representation for the distribution of the error term was considered. The test result shows that the test value of 78.79 is greater than 2.71. Therefore, the null hypothesis was rejected, suggesting that the random term has a truncated normal distribution.

Table 2: Statistics for Hypothesis Tests of the Stochastic Frontier Model

Null Hypothesis	Log likelihood		L-R test statistics	χ^2 critical value at 5%	Decision
Parameter restrictions $\alpha_{ij} = 0$ Quasi TL is adequate	H_0 12.285	H_1 21.952	19.334	24.384	Accept H_0: Quasi TL is adequate
$H_0 : \alpha_t = 0$ No technical change	12.285	14.023	3.476	2.708	Reject H_0
$H_0 : \eta = 0$ Inefficiency effects are time-invariant	100.925	0.575	200.700	2.708	Reject H_0
$H_0 : \mu = 0$ Half-normal distribution adequate	100.925	140.319	78.785	2.708	Reject H_0

Source: Own Estimates

Results and Discussion

The influence of Input Variables on Agricultural Production in African Countries

The maximum-likelihood estimates of the parameters in the Quasi-translog stochastic frontier production function model defined by equation (8) were obtained using FRONTIER 4.1 (Coelli, 1996). The maximum likelihood estimates for the parameters in the stochastic frontier are presented in Table 2. The signs of the estimated β-coefficients of the first order parameters of stochastic frontier were as expected. The coefficients of land, interaction of land and time were positive in all the countries of Africa. The coefficients of the labour variable and the interaction of labour and time were also positive across the continent. Also, the coefficients of livestock, interaction of livestock and time were found to be positive. These imply positive influence of these three input variables on agricultural production across the African countries. The coefficient of tractor was positive. However, the interaction of time and tractor was negative. The coefficient of the fertilizer variable was found to be negative. The interaction of time and fertilizer was however positive across countries. A possible explanation for these results could be that though fertilizer is known to increase agricultural production, excessive use of commercial fertiliser could cause soil damage. Similarly, the knowledge to use tractors at optimal levels may not be sufficient. But the coefficient of time and the square terms of time were estimated to be negative. These indicate technical regress across the countries studied. There is therefore, a possibility to increase the production by improving the use of available input resources.

Table 3: Maximum-likelihood Estimates for Parameters of Stochastic Frontier Model

Variable	Parameter	Coefficients
Constant	α_0	2.734 (2.776)
In land	α_1	0.089 (0.111)
In labour	α_2	0.676 (0.761)
In tractor	α_3	0.127 (0.258)
In fertilizer	α_4	-0.034 (-0.069)
In livestock	α_5	0.108 (0.196)
Time	α_6	-0.009 (-0.275)
0.5 Time*Time	α_7	-0.002 (-0.112)
Time*In land	α_8	0.001 (0.182)
Time*In labour	α_9	0.006 (0.249)
Time*In tractor	α_{10}	-0.007 (-0.256)
Time*In fertilizer	α_{11}	0.001 (0.092)
Time* Livestock	α_{12}	0.003 (0.225)
Sigma-Squared	σ^2	0.069 (1.583)
Gamma	γ	0.924 (1.130)

Source: Own Estimates *t-statistics are in brackets.

Variation in Output Explained by Random Disturbances in the Agricultural production of African countries

Using the composed error terms of the stochastic frontier model, as in equation (2), the random disturbances in the agricultural production of African countries was calculated by the error term. According to Omondi and Kelvin (2013), the composed error of the stochastic frontier production function causes the deviation from the frontier. FRONTIER Version 4.1 was used to calculate the error term from the stochastic frontier production by the method of maximum likelihood estimation (Coelli; 1996). This software utilizes the parameterisation from Coelli (1966) by replacing σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_{v_{it}}^2 + \sigma_{u_{it}}^2$ and the composed error term is defined by $\gamma = \sigma_{u_{it}}^2 / \left(\sigma_{v_{it}}^2 + \sigma_{u_{it}}^2\right)$, which is a measure of level of the inefficiency in the variance parameter it ranges between 0 and 1. The estimate of γ was 0.924 with estimated t-statistics of 1.130. This suggests that the value of γ is significantly different from one indicating that the percentage of the variation in output that is due to technical inefficiency is 92.4%. It was also observed that the value of sigma-squared (σ^2) was 0.069 with t-statistic of (1.150), implying that the agricultural industry stochastic random variation is also important in explaining the total variability of agricultural output produced. This was not unexpected in the African agricultural production where random disturbances are assumed to be possible sources of variation in output. However, African countries could still increase their agricultural production by about 8% at the given input use by developing new technology.

Conclusion:

The major objective of this paper was to apply the stochastic frontier production function approach to separate the effect of random variation in output from inefficiency in the agricultural production of African countries. A balanced panel data of 26 African countries, drawn from Food and Agriculture Organization covering the period 1961-2009 was used. The use of panel data, repeated observations on each production unit, generates information not provided by simply adding more producers to a cross-section data set (Breitung,2000). The general Cobb-Douglas and translog functional forms were tested for adequate functional form. The estimates of these two functional forms showed that the null hypothesis $H_0 : \beta_{ij} = 0$ could not be rejected; which indicates that the underlying stochastic production frontier function is best specified by a production function in generalized Cobb-Douglas form model. The function may be referred to as Quasi translog which can also be viewed as a translog specification without cross terms, i.e. a strongly separable-inputs translog production frontier function (Burhan et al 2009). The results and discussion of this paper were based on the Quasi-translog form. The parameters in the Quasi-translog stochastic frontier production function were estimated by the maximum-likelihood method using FRONTIER 4.1. The stochastic frontier incorporates stochastic output variability by means of a two-part error term. In order to separate deviations away from the frontier production function into random variation and inefficiency, a distribution assumption for both parts of the error term was imposed and the error term of the stochastic frontier calculated. The result of maximum likelihood estimates for the parameters in the stochastic frontier suggested that the signs of the estimated β-coefficients of the first order parameters of stochastic frontier were as expected. The coefficients of land, interaction of land and time were positive in all the countries of Africa. The coefficients of the labour variable and the interaction of labour and time were also positive across the continent. Also, the coefficients of livestock, interaction of livestock and time were found to be positive. These imply positive influence of these three input variables on agricultural production across the panel of African countries. Furthermore, the agricultural production function operated at a technical regress in a panel of African countries, there is therefore a possibility to increase the production by improving the use input resource. The γ variance parameter was significantly different from one at 0.924 indicating that the variation in output among African countries is explained by technical inefficiency. The σ^2 parameter was 0.076, implying that apart from inefficiency, agricultural industry stochastic random variation is playing a significant role in explaining the variation in agricultural production across the African countries. This is not unexpected in agricultural production where random shocks or measurement errors are assumed to be the main source of variation. However, it should be noted that though 92.4 % of the variation in production is due to technical inefficiency, African countries could still increase their agricultural output by about 7.6 % at given input variables.

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