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Production Efficiency of Pearl Millet Farming Households in Nigeria: A Translog Primal Cost System Approach

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Abstract Evidence on efficiency remains helpful in development and policy reform initiatives. Using a sample of 1,267 farming households from seven States in Nigeria, comprising 258 technology adopters and 1,009 non-adopters, an exponential translog stochastic frontier production function and primal cost system model were used to estimate production efficiencies. Adopters and non-adopters achieved 59% and 52% of maximum output, respectively. Male and female adopters were 59% and 50% technically efficient, respectively. Also, the elderly were more efficient in resource allocation. Accounting for input endogeneity, adopters and non-adopters attained 74% and 70% of minimum cost, separately. Adopters were more efficient than non-adopters demonstrating economic efficiencies of 44% and 37%, respectively. These outcomes underline the importance of extension agents having basic knowledge and skills of on improved technologies being promoted. Similarly, linkages between research and extension require strengthening and facilitation of access to credit to enable stakeholders take advantage of emerging economies of scale.

Keywords: *production efficiency, pearl millet technologies, cost system model*

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1. Introduction

Between 1995 and 2019, area under cultivation with pearl millet in Nigeria was estimated at 766,993,7 ha with a maximum of 643,830 ha in the Sahel savannah agroecological zone and minimum of 56,318.18 ha in the Guinea savannah agroecological zone [1]. Between 2020 and 2035, it is projected that area under cultivation will be constant while yield will be decreasing due to droughts, disease pressure and widespread poor soil fertility [2-6]. In the major pearl millet producing areas of northeast Nigeria, these challenges will be exacerbated by banditry, insurgencies and cattle rustling. Nonetheless, the gap between potential and actual pearl millet production has persisted over the years underlining challenges of inefficiencies and threats to the contributions of pearl millet to national food and nutrition security. Growth in agricultural production is explained by 67% and 33% improvements in productivity and factor deepening in developing countries [7], respectively. Against this background, improving production efficiency (PE) of resource-limited farming households becomes a critical instrument both for improving agricultural sector growth and, food and nutrition security [8].

Far into the deep future, the analysis of PE in agriculture will play a central role in research due to continued misallocation of resources by resource-limited farming households in developing countries [9,10,11,12,13]. The demand for pearl millet is expected to increase in Nigeria due to the fast-growing population of the country coupled with the need to address ongoing challenges of climate change and sustainable food production [14]. One of the strategies to ensure that pearl millet will indeed play a key role in food security and improvement of rural household livelihoods not only in Nigeria, but also in other developing countries, would be by raising their PE. This is probable because available data shows that farmers involved in the production of pearl millet around the globe have not been optimizing the use of limited resources. Average technical efficiency (TE) is around 30% in northern Namibia and 42% in Rajasthan, India. Although, statistics in PE of pearl millet farming remains scanty, there is consensus that farms under pear millet production in Nigeria, are highly inefficient, thereby offering opportunities for significant increase in current production levels [15,16,17,18,19]. For instance, TE lies between

0.21 and 0.48 [18] with allocative efficiency (AE) ranging from 0.55 to 0.91 in millet-based production systems in the derived Savanna agroecological zone of Nigeria while TE ranged between 21% and 94% among pearl millet farmers in Kano State [12].

PE has at least three prominent components namely: technical, allocative and economic (profit) which are critical for a comprehensive understanding of the production performance in rural area. Available literature is skewed towards examining TE of pearl millet farmers despite the fact that inputs are market-oriented [16,12,17]. The importance of allocative and economic efficiencies cannot be overlooked especially in a context where farmers are known to be constrained by limited access to capital and credit facilities. Few studies have evaluated the AE of pearl millet [18,20] using parametric and non-parametric methods in single equation frameworks such as stochastic frontier production (SFP) functions and Data Envelopment Analysis (DEA). Furthermore, state-of-art estimates of PE has been on a stand-by. [21] and [22] stated that production inputs are arguably endogenous especially in classical production, cost and profit functions in which estimates of PE would be biased. In order to contribute to literature on pearl millet technology adoption in Sub-Saharan Africa, and take advantage in addressing the endogeneity of factors of production, this paper uses the translog primal cost system (PCS) model to generate technical, allocative and economic efficiencies amongst pearl millet farmers in northern Nigeria. In so doing, the paper also incorporates sex (male-female) and age-group (youths, adults and elderly) differences in the estimation of different types of efficiencies.

2. Methodology

A four-stage sampling procedure was used with the first stage being the purposive selection of seven pearl millet producing states of northern Nigeria (Kano, Katsina, Sokoto, Jigawa, Kebbi, Bauchi and Yobe). The second stage was the selection of three Local Government Areas (LGAs) from each of the states where pearl millet technologies have been, and are still being promoted by research for development partners in Nigeria. This resulted in a total of 21 LGAs. In the third stage, four villages/communities were selected from each of the LGAs to give a total of 84. In the fourth and final stage of sampling procedure, a total of 1,267 pearl millet farmers were randomly sampled (Table 1). Despite the random sampling of pearl millet producing households, cautious efforts were made to identify and interview female pearl millet farmers in each community.

Table 1. Sample size and distribution of pearl millet producers across states

States	Men	Women	Totals
Bauchi	161	20	181
Jigawa	169	12	181
Kano	167	15	182
Katsina	173	7	180
Kebbi	163	18	181
Sokoto	168	13	181
Yobe	173	8	181
Totals	1,174	93	1,267
Percentage	(93%)	(7%)	(100%)

3. Model Specification

3.1. Stochastic Frontier Production Function

Relationships between inputs and outputs are expressed as:

$$y_{li} = f\left(x_i, \beta_j\right).\exp(\varepsilon_{ki}) \tag{1}$$

$$\varepsilon_{ki} = v_{ki} - u_{ki} \tag{2}$$

where $y_l \in \mathbb{R}_{++}$ is an $N \times l$ vector of outputs; $y_i \in \mathbb{R}_{+}$ is an $N \times j$ matrix of factors of production; $f(\bullet)$ is the optimal production practice; β_j is an $N \times j$ vector of regression parameters; $\exp(\bullet)$ is the exponential operator; ε_{ki} is a composite error term with u_{ki} and v_{ki} being the statistical and one-sided error terms, respectively; $l = 1, 2, ..., L$, $j = 1, 2, ..., J$ and $i = 1, 2, ..., N$ denote inputs used and outputs produced, respectively. Equations (1) and (2) are referred as the SFP function [23]; Taking the natural logarithm of (1) gives:

$$\ln y_{li} = \ln f\left(x_i, \beta_j\right) + v_{ki} - u_{ki} \tag{3}$$

v_{ki} is a symmetric and independently distributed (*i.i.d*) error term, which represents variability in output due to uncontrolled factors such as weather, pests and diseases, error of measurements and statistical noise.

u_{ki} represents the shortfall in output which is a deviation from the maximum output due to technical inefficiency (TI) implying that u_{ki} can be viewed as the proportion of observed output that can be increased using same inputs. In other words, u_{ki} is the proportion of actual output lost due to TI. Thus, u_{ki} is referred to as the output oriented TI with values ranging between 0 and 1 [24]. If its value is close to 1, the decision-making unit (DMU) is close to full TE, but when the value is close to 0 the DMU is close to full TI.

With proper handling, Kumbhakar [22] affirmed that the level of TE can be defined as:

$$TE_i = y_i \Big/ f\left(x_i, \beta_j\right).\exp(\varepsilon_{ki}) \tag{4}$$

[26], opined that based on the conditional mean function, the estimation of the DMU-specific TE conditional on the composite error term can be expressed as:

$$\begin{aligned} TE_i &= E\left(-u_i \middle| \varepsilon_i\right) \\ &= \sigma^* \left[f^*\left(\varepsilon_i \lambda / \sigma\right) \Big/ \left(1 - F^*\left(\varepsilon_i \lambda / \sigma\right)\right) \right] - \varepsilon_i \lambda / \sigma \end{aligned} \tag{5}$$

where $\sigma^* = \sigma_u^2 \sigma_u^2 / \sigma$; $\lambda = \sigma_u^2 / \sigma_v^2$; $f^*(\bullet)$ is the standard normal probability density function; $F^*(\cdot)$ is the standard cumulative density function and $\sigma^2 = \sigma_u^2 + \sigma_v^2$ is the variance of the composite error term; σ_u^2 is the variance of the one-sided error term assumed to be homoscedastic; σ_v^2 is the variance of the statistical noise assumed to be homoscedastic; σ^2 is the variance of the composite error term with a significant estimate indicating the correctness of model (1); λ is the relative variability between the statistical noise and the TI error where a positive and significant estimate implies that there is TI in the production process and that the difference between the actual and expected maximum output is dominated by TI [27]. Based on the λ parameterization by [23], the log-likelihood function of the model in [28] can be estimated as:

$$\ln(L) = -(N/2)\left(\ln 2\pi + \ln\sigma^2\right) + \sum_{i=1}^{N}\left[\ln\phi(\varepsilon\lambda/\sigma) - 1/2(\varepsilon_i/\sigma)^2\right] \tag{6}$$

According to [29], unlike the formulation of the log-likelihood function (LLF) using the γ parameterization, the LLF from (3) is derived as

$$\ln(L) = -(N/2)\left(\ln(\pi/2) + \ln\sigma^2\right) + \sum_{i=1}^{N}\left[1-\phi\left(\frac{z_i\sqrt{\gamma}}{\sigma^2}\sqrt{\frac{\gamma}{1-\gamma}}\right)\right] - \frac{1}{2\sigma^2}\sum_{i=1}^{N} z_i^2 \tag{7}$$

where z_i is a skewed normally distributed random variable; the gamma parameter $\left(\gamma = \sigma_u^2/\sigma^2\right)$ lies between 0 and 1 and should not be interpreted as the proportion of output produced that is accountable for by TI [22]; $\sum$ is the summation operator. If the value is significantly close to one, the production system is said to be influenced by technical inefficiencies, but if the value is significantly close to zero, the deviation from the frontier output is induced essentially by the statistical noise [15,22,30,31]. The maximum production function assumes several forms among which the most common are the CD and the translog function. The CD is nested into the translog, implying that the CD function can be viewed as a restricted version of the translog function.

In alignment with [30], the translog model is specified as

$$\ln y_i = \beta_0 + \sum_{j=1}^{J}\beta_j \ln x_{ji} + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\beta_{jk}\ln x_{ji}\ln x_{ki} + v_i - u_i \tag{8}$$

where y_i is the output, x_{1i}, x_{2i}, …, x_{ni} are inputs; β_j and β_{jk} are regression parameters; v_i is the statistical noise; u_i is the one-sided error term and $\ln$ is the natural logarithm operator. If $\sum\sum\beta_{jk} = 0$, the translog model reduces to the CD model, in which case the parameter β_j represents the output elasticity of the input *n*. Therefore, returns to scale is given by $\sum\beta_j$ where it will be decreasing, constant or increasing if $\sum\beta_j < 0$, $\sum\beta_j = 1$ or $\sum\beta_j > 0$, respectively. In order to test whether the CD is significantly nested in the translog model, the F-test and likelihood ratio (LR) test have been extensively used [30]; [22]. The test focuses on the joint null hypothesis that the parameters of the interaction terms in equation (8) are zero. The test procedure based on the F-test is to assess the closeness between the estimates of the sum of squares residuals (*SSR*) of the restricted (e.g., Cobb-Douglas) and unrestricted (Translog) models by means of the F-statistic which can be defined as:

$$F = \left[\left(SSR_R - SSR_U\right)/J\right]/\left[SSR/(N-K)\right] \tag{9}$$

where SSR_R is the SSR of the restricted model; SSR_U is the SSR of the unrestricted model; J is the number of restrictions; N is the number of observations in the sample; K is the number of restricted explanatory variables in the model. The null hypothesis is rejected at the $100\times\alpha\%$ level of significance if the estimate of the F-statistic exceeds the critical value $F_{1-\alpha}(J, N-K)$ in which case the translog model is preferred to the CD model as the more appropriate model for representing the relationship between inputs and outputs, otherwise the CD model is better; $F_{1-\alpha}(\cdot)$ is the standard cumulative density function; α is the level of significance. The LR test approach consists of evaluating the closeness between the estimates of the log-likelihood function (*LF*) of the restricted and unrestricted models via the LR statistic:

$$LR = \left(\ln LF_R - \ln LF_U\right) \sim \chi^2(J) \tag{10}$$

where LF_R is the LF of the restricted model; LF_U is the SSR of the unrestricted model; $\chi^2(\bullet)$ is a chi-square distribution function. The null hypothesis is rejected at the $100\times\alpha\%$ level of significance if the estimate of the LR statistic exceeds the critical value $\chi^2_{1-\alpha}(J)$ in which case the translog model is preferred to the CD model as the more appropriate model for representing the relationship between inputs and outputs, otherwise the CD model is better. If the translog is the preferred model, the output (production) elasticity of the input x_{ji} will be given as:

$$e_{x_{ji}} = \partial\ln y/\ln x_{ji} = \beta_j + \sum_{k=1}^{J}\beta_{jk}\ln x_{ki} \tag{11}$$

The implication of equation [32] is that the RTS of the translog function is not invariant of the initial input levels which is given as:

$$RTS = \sum_{j=1}^{J} Ex_{ji} = \sum_{j=1}^{J}\left(\beta_j + \sum_{k=1}^{J}\beta_{jk}\ln x_{ki}\right) \tag{12}$$

In equation (8) the distribution of the composite error term is not consistent with the error term in classical linear regression analysis which makes it impossible for ordinary least square estimator to be unbiased [31]. Different approaches have been proposed to estimate equation (8). These approaches are usually grouped into two categories namely, distribution free and distribution-based; each group has both advantages and disadvantages [22]. The distribution free approaches include the corrected Ordinary Least Square [5,22,33], the corrected mean absolute deviation [22] and the thick frontier approach [22,34]. The distribution-based approaches take on different distributions of statistical and the one-sided error terms. These approaches include single equations SFP and cost functions [22,23,35,36], stochastic frontier systems, primal cost and profit systems [22]. It should be noted that the translog SFP function presented in equation (8) was estimated as our main model in this study where y_i is the pearl millet yield (kg/ha); x_{1i} is the quantity of seed (kg/ha); x_{2i} is the quantity of inorganic fertilizer (kg/ha); x_{3i} is the quantity of organic fertilizer (l/ha); x_{4i} is the quantity of herbicide (l/ha); x_{5i} is the quantity of pesticide (l/ha) and x_{6i} is the quantity of labour (man-day/ha).

3.2. Stochastic Frontier Cost Function

A key objective of stochastic cost frontier analysis is to estimate the cost efficiency of DMUs. In order to do this, the actual and the minimum cost of production need to be identified. The actual cost of production (C^a) refers to the cost of production incurred by DMUs during the entire production process. The minimum cost of production (C^*) is from an optimization process, that is by solving a cost minimization challenge which can be expressed as:

$$\min\ w'x \quad s.t.\ \ y = f(xe^{-\zeta}) \tag{13}$$

where $f(\bullet)$ is the optimal production function that explains or predicts the technical relationship between inputs and output; e is the exponential operator; $\zeta \geq 0$ can be seen as the percentage of all overused inputs in producing y level of output (cost inefficiency). According to [22], $e^{-\zeta}$ represents the cost efficiency (CE) factor. The implication is that if a DMU uses a quantity of x input to produce y outputs, its cost-efficient quantity of input to produce the same level of output would be $x^e \equiv xe^{-\zeta}$. The first order condition required to solve the objective function in [15] can be stated as:

$$f_j(xe^{-\zeta}) \big/ f_1(xe^{-\zeta}) = w_j / w_1,\ \ j = 2,...,J, \tag{14}$$

where $f_j(\bullet)$ and $f_1(\bullet)$ are the partial derivatives of the input j and 1, respectively; w_j and w_1 are input prices of j and 1, respectively. By solving equation (14) for x_j where $j = 1,...,J$, the cost efficient quantities of the inputs, also known as input demand functions, are the quantities x_j adjusted for cost inefficiency (CI) which can be expressed as $x_j e^{-\zeta} = g_j(w,y)$, $j = 1,...,J$. Therefore, the minimum or frontier cost function which gives the minimum cost given input prices w and the observed level of output y can be expressed as:

$$C^*(w,y) = \sum\nolimits_j w_j x_j e^{-\zeta} \tag{15}$$

In order to relate the actual and minimum cost of production, [22] derived the following equation:

$$\ln C^a = \ln C^*(w,y) + \zeta \tag{16}$$

According to equation (16), the actual cost of production is increased by u since all inputs are overused by ζ. This shows that the AE also referred to as CE [37] of a DMU can be defined as:

$$AE = \exp(-\zeta) = C^* / C^a \tag{17}$$

By definition, AE is bounded between 0 and 1 which implies that $\zeta \geq 0$. The percentage increase in cost due to inputs' misallocation can therefore be given as:

$$AE = \left(C^a / C^*\right) - 1 = \exp(\zeta) - 1 \approx \zeta \tag{18}$$

AE equation (17) is greater than or equal to zero but ranges between 0 and 1 according to (18). In line with equation (18), if its estimate is equal to 1, the decision-making unit (DMU) is fully cost efficient, but if it is equal to 0 it the DMU is fully cost inefficient. This equally implies that estimate close to 1 and 0 indicates that the DMU is close to cost efficient and inefficient, respectively. Thus, $\zeta \times 100$ is the percentage by which the actual cost exceeds the minimum cost of production due to TI. Although either TE or AE is necessary to evaluate the PE of a firm, the occurrence of both TE and AE provides the sufficient condition under which EE can be evaluated [38]. According to [39], economic efficiency (EE) is the ability to achieve both technical and allocative efficiencies for a given output level. As opined by [30,39,40], EE, also known as overall efficiency by [32], is estimated as:

$$EE = TE \times AE \tag{19}$$

Assuming a translog specification on $\ln C^*(w,y)$ and the appending random error, equation (16) can be re-written as:

$$\begin{aligned} \ln C^a &= \alpha_0 + \alpha_y \ln y_i + \sum\nolimits_j \alpha_j \ln w_{ji} \\ &\quad + \tfrac{1}{2}\alpha_{yy} \ln y_i \ln y_i + \tfrac{1}{2}\sum\nolimits_j \sum\nolimits_k \alpha_{jk} \ln w_{ji} \ln w_{ki} \\ &\quad + \sum\nolimits_j \alpha_{yj} \ln y_i \ln w_{ji} + v_i + \zeta_i \end{aligned} \tag{20}$$

where α_0, α_y, α_j, α_{yy}, α_{jk} and α_{yj} are regression parameters; v_i is a statistical noise assumed to be normally distributed with zero mean and a constant variance; v_i is a one-sided error term that can assume different distributions such as exponential, half-normal, gamma and truncated normal distribution. Equation (20) is known as the translog stochastic frontier cost (SFC) function. Equation (20) could be reduced to the CD stochastic frontier function if $\sum_j \alpha_{jk} = 0\ \forall k$, and $\sum_j \alpha_{yj} = 0$. Thus, this restriction can equally be tested using the F-test and the LR test as shown previously. But a cost function as presented in equation (20) should be homogenous, which can be obtained by normalizing the total cost and input prices by normalizing input price. The input shares are similar to cost elasticities and are defined based on equation (20) as:

$$e_{p_{ji}} = \partial \ln C / \partial \ln w_{ji} = \alpha_s + \sum_j \alpha_{sj} \ln w_{ji} + \alpha_{ys} \ln y_i,\ s = 1,2,...,J \quad (21)$$

$$e_{y_{ji}} = \partial \ln C / \partial \ln y_i = \alpha_y + \sum_j \alpha_{yy} \ln y_{ji} + \alpha_{yj} \ln w_{ji},\ j = 1,2,...,J \quad (22)$$

In the light of the above, the normalized exponential, half-normal and truncated translog SFC functions for pearl millet production was specified and estimated, respectively, as:

$$\ln \tilde{C}^a = \alpha_0 + \alpha_y \ln y_i + \sum_{j=1}^{6} \alpha_j \ln \tilde{w}_{ji} + \tfrac{1}{2}\alpha_{yy} \ln y_i \ln y_i + \tfrac{1}{2}\sum_{j=1}^{6}\sum_{k=1}^{6} \alpha_{jk} \ln \tilde{w}_{ji} \ln \tilde{w}_{ki} + \sum_{j=1}^{7} \alpha_{yj} \ln y_i \ln \tilde{w}_{ji} + v_i + \zeta_{1i} \quad (23)$$

$$\ln \tilde{C}^a = \alpha_0 + \alpha_y \ln y_i + \sum_{j=1}^{6} \alpha_j \ln \tilde{w}_{ji} + \tfrac{1}{2}\alpha_{yy} \ln y_i \ln y_i + \tfrac{1}{2}\sum_{j=1}^{6}\sum_{k=1}^{6} \alpha_{jk} \ln \tilde{w}_{ji} \ln \tilde{w}_{ki} + \sum_{j=1}^{7} \alpha_{yj} \ln y_i \ln \tilde{w}_{ji} + v_i + \zeta_{2i} \quad (24)$$

$$\ln \tilde{C}^a = \alpha_0 + \alpha_y \ln y_i + \sum_{j=1}^{6} \alpha_j \ln \tilde{w}_{ji} + \tfrac{1}{2}\alpha_{yy} \ln y_i \ln y_i + \tfrac{1}{2}\sum_{j=1}^{6}\sum_{k=1}^{6} \alpha_{jk} \ln \tilde{w}_{ji} \ln \tilde{w}_{ki} + \sum_{j=1}^{7} \alpha_{yj} \ln y_i \ln \tilde{w}_{ji} + v_i + \zeta_{3i} \quad (25)$$

where $\tilde{C}_i^a = \sum_{j=1}^{7} \left(w_j x_{ji} / w_{7i} \right) =$ Normalized cost of pearl millet production (₦) $y_i =$ Pearl millet yield (kg/ha); $\tilde{w}_{1i} = w_{1i} / w_{4i} =$ Normalized price of land (₦/kg); $\tilde{w}_{2i} = w_{2i} / w_{4i} =$ Normalized price of seeds (₦/kg); $\tilde{w}_{3i} = w_{3i} / w_{4i} =$ Normalized price of fertilizer (l/ha); $w_{4i} =$ Price of labour (₦/man-day); $v_i \sim N\left(0, \sigma_v^2\right)$; $\zeta_{1i} \sim N\left(0, \sigma_{1\zeta}^2\right)$; $\zeta_{2i} \sim N^+\left(0, \sigma_{2\zeta}^2\right)$; $\zeta_{3i} \sim N^+\left(0, \sigma_{3\zeta}^2\right)$. The parameters in equations (23) through (25) can be estimated through the maximization of the log-likelihood functions, respectively:

$$L_i = -\ln(\eta) + \ln\left[\Phi\left(-\frac{\varepsilon_i}{\sigma_v} - \frac{\sigma_v}{\eta}\right)\right] + \frac{\varepsilon_i}{\eta} + \frac{\sigma_v^2}{2\eta^2} \quad (26)$$

$$L_i = -\ln\left(\frac{1}{2}\right) - \frac{1}{2}\ln\left(\sigma_v^2 + \sigma_\zeta^2\right) + \ln\phi\left(\frac{\varepsilon_i}{\sqrt{\sigma_v^2 + \sigma_\zeta^2}}\right) + \ln\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right) \quad (27)$$

$$L_i = -\frac{1}{2}\ln\left(\sigma_v^2 + \sigma_\zeta^2\right) + \ln\phi\left(\frac{\mu + \varepsilon_i}{\sqrt{\sigma_v^2 + \sigma_\zeta^2}}\right) + \ln\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right) - \ln\Phi\left(\frac{\mu}{\sigma_\zeta}\right) \quad (28)$$

3.3. Primal Cost System Model

Equations (21) through (23) will only be justified if CI terms are statistically different from zero, that is if the actual cost of production is significantly different from its "true" or estimated minimum cost. Theoretically, an important feature of the cost function is that it increases with increase in inputs prices. But in a single equation framework, there is no guarantee that the cost function will be well-behaved in ensuring that the relationship between the cost of production and input prices is positive. In order to overcome this limitation, a full cost dual function with shared equations were simultaneously estimated as a multivariate system [22,24,42]. According to [22], the empirical model is specified as:

$$\begin{aligned}
\ln \tilde{C}^a &= \alpha_0 + \alpha_y \ln y_i + \alpha_1 \ln \tilde{w}_{1i} + \alpha_2 \ln \tilde{w}_{2i} + \alpha_3 \ln \tilde{w}_{3i} + \tfrac{1}{2}\alpha_{yy} \ln y_i \ln y_i + \tfrac{1}{2}\alpha_{11}\left(\ln \tilde{w}_{1i}\right)^2 \\
&+ \tfrac{1}{2}\alpha_{22}\left(\ln \tilde{w}_{2i}\right)^2 + \tfrac{1}{2}\alpha_{33}\left(\ln \tilde{w}_{3i}\right)^2 + \alpha_{12} \ln \tilde{w}_{1i} \ln \tilde{w}_{2i} \\
&+ \alpha_{13} \ln \tilde{w}_{1i} \ln \tilde{w}_{3i} + \alpha_{23} \ln \tilde{w}_{2i} \ln \tilde{w}_{3i} + \alpha_{y1} \ln y_i \ln \tilde{w}_{1i} \\
&+ \alpha_{y2} \ln y_i \ln \tilde{w}_{2i} + \alpha_{y3} \ln y_i \ln \tilde{w}_{3i} + v_i + \tilde{\zeta}_i \\
s_{1i} &= \alpha_1 + \alpha_{11} \ln \tilde{w}_{1i} + \alpha_{12} \ln \tilde{w}_{2i} + \alpha_{13} \ln \tilde{w}_{3i} + \alpha_{y1} \ln y_i + v_{1i} \\
s_{2i} &= \alpha_2 + \alpha_{12} \ln \tilde{w}_{1i} + \alpha_{22} \ln \tilde{w}_{2i} + \alpha_{23} \ln \tilde{w}_{3i} + \alpha_{y2} \ln y_i + v_{2i} \\
s_{3i} &= \alpha_3 + \alpha_{13} \ln \tilde{w}_{1i} + \alpha_{23} \ln \tilde{w}_{2i} + \alpha_{33} \ln \tilde{w}_{3i} + \alpha_{y3} \ln y_i + v_{3i}
\end{aligned} \quad (29)$$

where $s_{1i} = w_1 x_1 / C^a =$ Cost share of land; $s_{2i} = w_2 x_2 / C^a =$ Cost share of seed; $s_{3i} = w_3 x_3 / C^a =$ Cost share of fertilizer; $v_i \sim N^+\left(0, \sigma_v^2\right)$; $\omega = (v_i, v_{1i}, v_{2i}, v_{3i})' \sim N(0, \Omega)$. Note that $\sum_{j=1}^{7} s_{ji} = 1$ with $s_{4i} = w_4 x_4 / C^a =$ Cost share of labour. The fourth shared equation (s_{4i}) was intentionally dropped to avoid the problem of singular covariance matrix [25]. Based on the Cholesky decomposition, the covariance matrix Ω can be assumed to be constant, partially heteroscedastic, and fully heteroscedastic and is expressed as $\Omega = LL'$ where L is a lower triangular matrix. Assuming that the partial heteroscedasticity (correlation) between v_i and ω is such that:

$$L = \begin{bmatrix} \exp(s11) & 0 & 0 & 0 \\ 0 & \exp(s22) & 0 & 0 \\ 0 & \exp(s32) & \exp(s33) & 0 \\ 0 & \exp(s42) & \exp(s43) & \exp(s44) \end{bmatrix} \quad (30)$$

where the parameters $s11 \cdots s44$ are to be estimated, equation (29) was estimated by maximizing the following log-likelihood function [44]:

$$LF = N \ln 2 - NJ/2 \ln(2\pi) - NJ/2 \ln|\Omega| + N \ln \sigma \sum_i \Phi\left(Z_i' \Omega^{-1} d\sigma\right) - N \ln \sigma_v ?(1/2) \sum_i a_i \quad (31)$$

where

$$\sigma^2 = \left(1/\sigma_v^2 + d'\Omega^{-1}d\right)^{-1};$$

$$a_i = Z_i'\Omega^{-1}Z_i - \sigma^2\left(Z_i'\Omega^{-1}d_i\right)^{-1};$$

$\Phi(\bullet) =$ cumulative distribution function of a standard normal variable; $\sum$ is a 2×2 diagonal matrix. AE according to equation (29) was determined [22]:

$$\psi = \left\{\left(1-\Phi\left[\sigma-\left(\tilde{\mu}/\sigma\right)\right]\right)/\Phi\left(\tilde{\mu}/\sigma\right)\right\}\times\exp\left(-\tilde{\mu}+\tfrac{1}{2}\sigma^2\right) \quad (32)$$

where $\tilde{u}_i = Z_i'\Omega^{-1}d_i\sigma^2$. Based on equation (29), the scale economy (SCE) was given as [25]:

$$SCE = 1-\partial\ln\tilde{C}^a/\partial\ln y_i \quad (33)$$

If SCE is positive, economies of scale occur, if it is negative there are diseconomies of scale [25], but if it is zero, there is constant return to scale. A positive economy of scale implies that large-scale production is feasible in order to capture scale (efficiencies) if cost declines as output increases [45]. On the other hand, if unit cost increases as output increases, smaller scale of production may be required to capture production efficiencies.

4. Results and Discussion

As indicated in Table 2, about 20% of the respondents of the survey were adopters of at least one of the four improved pearl millet varieties being promoted (SOSAT-C88, SUPER-SOSAT, JIRANI and LCIC 9702). These adoption levels are considered to be low and in agreement with the adoption level of improved millet variety reported by [46,47,48] in northern Nigeria. In a broader perspective, these results could also be explained by the scale of production and level of exposure to the technologies being promoted [46]. However, the results are consistent with the fact that the adoption of agricultural technologies remains low in Sub-Saharan Africa [49,50,51,52]. Average yield was 1,121 kg/ha with that of adopters and non-adopters being 1,212 kg/ha and 1,068 kg/ha, respectively revealing a yield gap of 444 kg/ha. Such a bivariate comparison is likely to be biased given that farmers' characteristics may have contributed to the yield difference [46]. However, the results agree with the hypothesis that adoption of improved technologies tend to increase crop yields.

Mean cost of production was ₦130,229/ha with an insignificant difference between adopters and non-adopters. Similarly, there was no difference between adopters and non-adopters for farm size, seeds, fertilizer, herbicide and pesticide on a hectare basis. Farmer cultivated 1.15 ha of land with 93kg of seeds, 185kg of inorganic fertilizer, 1,861kg of organic fertilizer, 3 litres of herbicide and 1.5 litres of pesticide. Input prices were practically the same for adopters and non-adopters except for labour, perhaps indicating the competitiveness of the input segment of the pearl millet value chain. A total of ₦55,340 was spent to cultivate one hectare of land, ₦60/kg, ₦150/kg, ₦1,010/litre, ₦1,200/litre and ₦680/man-day was spent on seeds, inorganic fertilizer, organic fertilizer, herbicides, pesticides and labour, respectively. Majority of respondents were men (93%) with mean age of 44 years, suggesting that respondents were relatively young. This is a huge advantage in terms of faster comprehension of the intricacies of adoption of improved technologies. The distribution of farmers by state shows that adopters were from Jigawa State (34%), Kano State (21%) and Katsina State (18%). Also, there was a significant difference in adoption status across all the States except in Bauchi where there were 14% of adopters and non-adopters. Adopters planted the four improved pearl millet varieties being promoted in Nigeria namely SOSAT-C88 (69%) followed by SUPER SOSAT (26%), JIRANI (5%) and LCIC-9702 (3%). Accounting for differences in socio-economic characteristics, an adequate econometric analysis would probably reveal the performance of adopters and non-adopters of the improved pearl millet varieties being promoted.

4.1. Production Elasticities and Returns to Scale

An important step in the analysis of PE is the identification of an appropriate model based on observed dataset. Misspecification will likely yield the wrong frontier in which case the performance would either be overestimated or underestimated. According to Table 3, the null hypothesis that there is no difference between CD and translog SF (exponential, half-normal and truncated) was significant, meaning that the null hypothesis was rejected. In other words, the production technology exhibited a translog form. Moreover, the rejection of the null hypothesis evidenced the presence of a one-sided error term, that is the actual production of pearl millet deviated from its expected maximum essentially due to TI. However, a discriminatory assessment of the distribution of the one-sided error term revealed that the exponential SFP function was better than the half-normal and truncated SFPF. This implies that the exponential SFP function was the most appropriate model for explaining the relationship between inputs and outputs of pearl millet as a cereal crop [53,54]. Furthermore, the hypothesis that the production function of pearl millet for adopters was the same as that of the non-adopters was rejected at 1% level of probability implying that the exponential translog SFP functions should be estimated for adopters and non-adopters separately.

The maximum likelihood (ML) estimates of the exponential translog for pearl millet for both adopters and non-adopters are presented in Table 4. The Wald statistic for adopters (Wald =571.29, p<0.01) and non-adopters (Wald =988.06, p<0.01) are statistically significant at 1% level of probability, implying that factors of production jointly influenced pearl millet yield among adopters and non-adopters. The estimates of lambda for the pooled (λ=1.14, p<0.01), adopters (λ=3.19, p<0.01) and non-adopters (λ=1.23, p<0.01) were equally positive and significant at 1% level of probability. These findings confirmed previous results that there is TI for both adopters and non-adopters [16,20] and [12] who showed that the maximum pearl millet yield is not achieved due to TI. Further interpretation of the model is quite complicated given the non-linearity nature of the relationship between inputs and outputs which can be simplified by assessing the output elasticity of inputs used.

Yield elasticity of the use of seeds relative to farm size was -1.26. and is significant at 1% level of probability implying that there was an indirect relationship between yield and quantity of seeds planted and that pearl millet yield was elastic to changes in the quantity of seed rates (Table 5). Therefore, if quantity of seeds increases by 1%, yield would decrease by 1.26%, holding other variables constant. This finding is contrary to *a priori* expectation and was perhaps due to farmers' failure to adhere to recommended seed rate and agronomic practices. Only few adopters treated their seeds according to recommended practices though seed dressing has an advantage in terms of yield increase, pest and disease control [55]. This is in agreement with [3] who opined that majority of farmers in northern Nigeria do not dress seeds before planting due to scarcity and/or high cost of seed dressing chemicals. The elasticity of yield to seeds for adopters and non-adopters was -1.3 and -1.41, respectively, holding other variables constant. The implication is that mishandling of seeds and perhaps failure to stay within the optimum planting density were common challenges with both adopters and non-adopters. This is in line with [56] who observed that seed rates had a negative influence on rice output in Sagnarigu District of Ghana.

Table 2. Descriptive statistics of the data used

Variable	Definitions and measurement units	Pooled (N=1,267)	Adopters (n_1=258)	Nonadopters (n_2=1,009)	Mean Diff.
Output	Pearl millet harvested (kg/ha)	1,121 (558)	1,212 (1,168)	1,068 (567)	1.70*
Cost	Cost of prod. (₦/ha)	130,229 (9,370)	131,520 (8,780)	129,900 (9,520)	-0.24
Land	Land size cultivated (ha)	1.15 (1.04)	1.24 (1.29)	1.13 (0.97)	-1.52
Seed	Seed used (kg/ha)	93 (444)	86 (109)	95 (495)	0.27
In. Fert	Inor. Fert. used (kg/ha)	185 (199)	193 (179)	183 (204)	-0.73
Or. Fert	Org. fert. used (kg/ha)	1,861 (2,007)	1,918 (1,961)	1,847 (2,019)	-0.51
Herb.	Herbicide used (litre/ha)	3 (3)	3.08 (3.4)	3 (2)	-1.34
Pest.	Pesticide used (litre/ha)	1.5 (2)	1.58 (2.09)	1.44 (2)	-1.05
Labour	Labour used (man-day/ha)	43 (58)	45 (46)	42 (60)	-0.66
PLand	Price of land (₦/ha)	55,340 (2,115)	53,751 (2,035)	55,751 (2,135)	1.35
PSeed	Price of seed (₦/kg)	60 (50)	70 (70)	60 (40)	-0.79
PInoFert	Price of inorg. Fert. (₦/kg)	150 (40)	150 (40)	150 (40)	-0.74
PorgFert	Price of organ. Fert. (₦/kg)	7 (6)	7 (4)	10 (10)	0.93
PHerb.	Price of herbicide (₦/litre)	1010 (450)	1050 (470)	1000 (450)	-1.55
PPest.	Price of pesticide (₦/litre)	1200 (590)	1140 (595)	1210 (580)	1.63
Plab.	Price of labour (₦/man-day)	680 (120)	670 (120)	690 (120)	2.29**
Sex	Household is male (1=Yes)	0.93 (0.26)	0.97 (0.16)	0.91 (0.28)	-3.2***
Age	Age of hld head (Years)	44 (13)	45 (13)	44 (13)	-1.62
Bauchi	Farm is in Bauchi (1=Yes)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)	-0.03
Jigawa	Farm is in Jigawa (1=Yes)	0.14 (0.35)	0.34 (0.47)	0.09 (0.29)	-10.41***
Kano	Farm is in Kano (1=Yes)	0.14 (0.35)	0.21 (0.41)	0.13 (0.33)	-3.58***
Katsina	Farm is in Katsina (1=Yes)	0.14 (0.35)	0.18 (0.39)	0.13 (0.34)	-2.07***
Kebbi	Farm is in Kebbi (1=Yes)	0.14 (0.35)	0.05 (0.21)	0.17 (0.37)	5***
Sokoto	Farm is in Sokoto (1=Yes)	0.14 (0.35)	0.03 (0.17)	0.17 (0.38)	5.83***
Yobe	Farm is in Yobe (1=Yes)	0.14 (0.35)	0.05 (0.21)	0.17 (0.37)	5.83***
SOSAT	Adopt. of SOSAT (1=Yes)	0.14 (0.35)	0.69 (0.46)	0	-47.78***
SSOSAT	Adopt. of SSOSAT (1=Yes)	0.05 (0.23)	0.26 (0.44)	0	-18.9***
JIRANI	Adopt. of JIRANI (1=Yes)	0.01 (0.10)	0.05 (0.23)	0	-7.60***
LCIC	Adoption of LCIC (1=Yes)	0.01 (0.07)	0.03 (0.16)	0	-5.3***
Adoption	Adopter of a least 1 improved variety (1=Yes)	0.20 (0.40)	0.20 (0.40)	0	-

***<0.01; **<0.05 and *<0.1; () Standard deviations.

Table 3. Likelihood ratio test for the specification of the production function for pearl millet

Test	Null hypothesis	LR	χ^2	Decision
1	OLS Cobb-Douglas Vs OLS translog	195.52***	38.30	Rejected
2	OLS translog Vs SF Expon. Translog	122.43***	5.41	Rejected
3	OLS translog Vs SF Half-normal translog	66.7***	5.41	Rejected
4	OLS translog Vs SF Truncated translog	122.35***	8.273	Rejected
5	SF Expon. translog Vs SF Half-normal translog	-55.73	1.642	Accepted
6	SF Expon. translog Vs SF Truncated translog	-0.0831	3.808	Accepted
7	Adopters Vs non-adopters	150.1***	45.35	Rejected

***<0.01; OLS=Ordinary Least Squares; SF=Stochastic Frontier.

Table 4. Maximum likelihood estimates of exponential translog stochastic frontier production function

Variable	Parameter	Pooled	Adopters	Nonadopters
Constant	β_0	4.41 (10.29)	118.24 (48.69)**	11.86 (10.68)
Qty of seed	β_1	-15.87 (2.04)***	-49.74 (9.94)***	-19.05 (2.33)***
Qty of inorganic fert.	β_2	1.92 (1.59)	-1.75 (4.29)	2.04 (1.7)
Qty of organic fert.	β_3	-0.87 (1.18)	-9.96 (4.75)**	-0.39 (1.2)
Qty of herbicide	β_4	-1.09 (2.97)	-27.87 (7.09)***	-0.82 (3.34)
Qty of pesticide	β_5	2.43 (2.14)	-7.26 (4.54)	6.05 (2.31)***
Qty of labour	β_6	19.44 (5.97)***	25.33 (15.11)*	18.05 (6.31)***
0.5* Qty of seed^2	β_{11}	2.24 (0.48)***	3.72 (1.33)***	3.17 (0.52)***
0.5* Qty of inor. Fert^2	β_{22}	0.42 (0.11)***	0.59 (0.28)**	0.36 (0.12)***
0.5* Qty of org. Fert^2	β_{33}	0.26 (0.12)**	0.75 (0.26)***	0.2 (0.12)*
0.5* Qty of herb^2	β_{44}	-0.61 (0.41)	-3.51 (0.65)***	0.25 (0.49)
0.5* Qty of pest^2	β_{55}	1.27 (0.26)***	0.89 (0.48)*	1.23 (0.27)***
0.5* Qty of lab^2	β_{66}	-3.71 (1.64)**	-12.11 (3.74)***	-3.76 (1.76)**
Qty of seed*Inor. Fert.	β_{12}	0.52 (0.12)***	0.73 (0.36)**	0.52 (0.13)***
Qty of seed*Org. Fert.	β_{13}	0.39 (0.16)***	1.71 (0.53)***	0.18 (0.16)
Qty of seed*Herbicide	β_{14}	-0.45 (0.36)	0.44 (0.86)	-0.24 (0.39)
Qty of seed*Pesticide	β_{15}	-0.95 (0.28)***	1.75 (0.62)***	-1.6 (0.31)***
Qty of seed*Labour	β_{16}	0.12 (0.59)	4.57 (1.63)***	0.29 (0.6)
Qty of inor. *Org. Fert.	β_{23}	-0.17 (0.06)***	-0.13 (0.15)	-0.14 (0.06)**
Qty of inor. Fert.*Herb.	β_{24}	-0.58 (0.16)***	0.03 (0.58)	-0.85 (0.17)***
Qty of inor. Fert.*Pest,	β_{25}	-0.04 (0.1)	0.14 (0.23)	-0.05 (0.1)
Qty of inor. Fert.*Lab.	β_{26}	-1.12 (0.37)***	-0.87 (0.92)	-1.06 (0.42)***
Qty of org. fert.*Herb.	β_{34}	-0.06 (0.15)	0.07 (0.34)	0.1 (0.16)
Qty of org. fert.*Pest.	β_{35}	0.2 (0.09)**	0.16 (0.18)	0.08 (0.1)
Qty of org. fert.*Lab.	β_{36}	-0.43 (0.21)**	-0.45 (0.71)	-0.3 (0.22)
Qty of herb.*Pest.	β_{45}	-1.13 (0.21)***	-1.81 (0.44)***	-0.76 (0.22)***
Qty of herb.*Labour	β_{46}	2.18 (0.55)***	8.16 (1.14)***	1.68 (0.59)***
Qty of pest.*Labour	β_{56}	0.3 (0.37)	0.12 (0.69)	0.15 (0.39)
Sigma_u	σ_u	0.59 (0.04)***	0.79 (0.07)***	0.59 (0.04)***
Sigma_v	σ_v	0.52 (0.02)***	0.25 (0.04)***	0.48 (0.03)***
Lambda	λ	1.14 (0.05)***	3.19 (0.09)***	1.23 (0.06)***
Log-likelihood		-1449.17	-265.99	-1108.13
Wald chi2(35,)		1004.75***	571.29***	988.06***
Number of observations		1267	258	1009

***<0.01, **<0.05, and *<0.1; () standard errors in brackets; Input quantities and output are in natural logarithm.

The yield elasticity of inorganic fertilizer was 0.35 and significant at 1% level of probability, indicating that there was a positive relationship between application of inorganic fertilizer and yield; also, yield was inelastic to changes in inorganic fertilizer. If inorganic fertilizer increases by 1%, yield would increase by 0.35%, all things being equal. Similarly, there was a positive and inelastic relationship between yield and use of organic fertilizer such that an increase in the use of organic fertilizer by 1% would induce a growth in yield of 0.19%, all things being equal. It can also be said that there was a direct relationship between yield and use of fertilizer among both adopters and non-adopters of improved pearl millet technologies. The finding is in line with *a priori* expectation given that fertilizer application improves soil fertility when applied appropriately. This is in agreement with [57,58] and [59] who reported that fertilizer application increases yield in pearl millet production. According to [59], the application of poultry manure at a rate of 1.6 and 2.4 t/ha, for example, increased pearl millet yield by 56% in Niger, but when combined with 40kg of NPK fertilizer, yield doubles. In fact, according to [57], micro-dosing with inorganic fertilizer can increase yields regardless of the timing of application.

Weeds are usually managed either by manual removal or chemical application [60]. There was a positive and significant influence of herbicide application on pearl millet yield, suggesting that pearl millet farmers effectively controlled weeds through the application of pre-emergence herbicides given that the application of recommended doses by 1% would result in yield increase of about 0.77%. Also, [60], reported that the application of pre-emergence herbicide together with one manual weeding can provide satisfactory weed management. Furthermore, [61] reported that proper application of herbicide increased yields in pearl millet production in Sokoto state of Nigeria. While the effect of pesticide and labour on yield was positive and significant among adopters, their effect was negative and significant among non-adopters. This highlights the fact that adopters and non-adopters applied pesticide differently. Pests pose an important challenge to farmers who do not often possess adequate capacities in the application of pesticides in pearl millet farming. These findings agree with those of [62] who pointed out that although insecticides can be economical under high-inputs agriculture, their misuse can have negative health and environmental consequences.

The RTS estimate was -0.27, indicating that there was a decreasing RTS (DRTS) in pearl millet production. The significance of the assumption of CRTS was rejected at 1% probability level indicating that doubling all inputs would less than double output, all things being equal. In a similar connection, [63] equally found that there was an DRTS among pearl millet farmers in Niger state, Nigeria. The estimates of the RTS among adopters and non-adopters were 0.62 and -0.72, respectively. Although both estimates were less than 1, the hypothesis of constant RTS (CRTS) was only rejected for non-adopters. In other words, pearl millet production among adopters exhibited a CRTS, but a DRTS among the non-adopters, provides further evidence that adopters and non-adopters allocated inputs differently.

4.2. Technical Efficiency

Table 6 shows a pooled TE of 0.54, implying that pearl millet farmers included the survey achieved 54% of expected output. In other words, 46% of the expected output was lost due to technical inefficiencies. The estimate of TE is below 81% TE of pearl millet production in Kano state, Nigeria reported by [12], but falls within the range of 52%-79% TE reported by [18] millet-based farming systems in the derived Savanna zone of Nigeria. The higher TE reported by [12] could be explained by the use of the DEA, a methodology which links all deviations from maximum output to TI and does not account for statistical noise [64,65,66]. Similarly, [12] used the CD stochastic frontier production function with same dataset and came out with a mean TE of pearl millet farmers in Kano state of 71%.

TE was 0.59 and 0.52 for adopters and non-adopters of pearl millet technologies, respectively implying that 59% and 52% of expected outputs were attained by each group of adopters. TE of the least and most efficient farmer was 0.01 and 0.97, respectively suggesting that the least technically efficient pearl millet farmers can still increase output by 99 percent with existing level of inputs while the most technical efficient farmer can still increase production by 3% percent using the same level of inputs. In a nutshell, adopters were more technically efficient than non-adopters, though the difference was not quite important. However, the difference in TE between adopters and non-adopters does not have any causal interpretation considering that adopters and non-adopters were different in socio-economic scharacteristics. Other authors, [67,68] and [28] showed that adopters of improved cereal crops were significantly more technically efficient than non-adopters after accounting for observed and/or unobserved characteristics.

The distribution of TE by sex and state of the survey revealed exciting outcomes. Firstly, there are variations across states and between male and female respondents, possibly attributed to differences in socio-economic profiles (Table 7). Secondly, male and female respondents demonstrate different drives to achieving expected outputs with available inputs. Male and female adopters, for example, were 59% and 50% technically efficient, respectively revealing a difference in TE of 9%. Also, male and female non-adopters were about 52% technically efficient. Overall, adopters were more technically efficient than non-adopters across states. Female respondents in Katsina state were the most technically efficient while male respondents in Jigawa sttate were the most technically efficient. Katsina state was the most technically efficient state (57%) followed by Bauchi and Kano states, each with 54% TE. The policy implication here is the imperative for a sex-based approach in extension service delivery in the promotion of pearl millet farming in Nigeria [12,46].

Table 5. Estimates of the output elasticities and returns to scale

Variable	Parameter	Pooled	Adopters	Nonadopters
Quantity of seed	e_{x1}	-1.26 (0.119)***	-1.3 (0.25)***	-1.41 (0.13)***
Quantity of inorganic fertilizer	e_{x2}	0.348 (0.058)***	0.13 (0.12)	0.37 (0.06)***
Quantity of organic fertilizer	e_{x3}	0.188 (0.042)***	0.32 (0.09)***	0.11 (0.04)**
Quantity of herbicide	e_{x4}	0.767 (0.103)***	0.48 (0.23)**	0.82 (0.11)***
Quantity of pesticide	e_{x5}	-0.101 (0.053)*	0.52 (0.09)***	-0.24 (0.06)***
Quantity of labour	ex_6	-0.209 (0.194)	0.47 (0.38)	-0.37 (0.21)*
Return to Scale	RTS	-0.263 (0.27)	0.62 (0.59)	-0.72 (0.29)**
RTS =1		-1.263 (0.27)***	-0.38 (0.59)	-1.72 (0.29)***

***<0.01, **<0.05, and *<0.1; () Standard errors in brackets.

Table 6. Technical efficiency based on adoption status

	Pooled		Adopters		Non-adopters	
Eff. Class	Freq	Percent	Freq	Percent	Freq	Percent
<0.21	67	5.29	18	6.98	49	4.86
0.21-0.40	265	20.92	41	15.89	224	22.2
0.41-0.60	479	37.81	74	28.68	405	40.14
0.61-0.80	327	25.81	71	27.52	256	25.37
0.81-1.00	129	10.18	54	20.93	75	7.43
Total	1,267	100	258	100	1009	100
Mean	0.54		0.59		0.52	
Std deviation	0.20		0.24		0.19	
Min	0.01		0.02		0.01	
Max	0.97		0.97		0.93	

Table 7. Technical efficiency based on sex and adoption status

	Women			Men			Pooled		
State	Pooled	AD	Nona	Pooled	AD	Nona	Pooled	AD	Nona
Bauchi	0.50	0.00	0.50	0.54	0.58	0.53	0.54	0.58	0.53
Jigawa	0.55	0.44	0.57	0.58	0.63	0.52	0.57	0.62	0.53
Kano	0.51	0.36	0.53	0.54	0.57	0.53	0.54	0.56	0.53
Katsina	0.57	0.59	0.56	0.52	0.56	0.51	0.53	0.56	0.51
Kebbi	0.52	0.75	0.51	0.51	0.59	0.51	0.51	0.60	0.51
Sokoto	0.54	0.00	0.54	0.53	0.56	0.52	0.53	0.56	0.52
Yobe	0.48	0.00	0.48	0.53	0.61	0.53	0.53	0.61	0.53
Total	0.52	0.50	0.52	0.54	0.59	0.52	0.54	0.59	0.52

AD=Adopters; Nona=Non-adopters.

Table 8. Descriptive statistics of technical efficiency

	Pooled		Youths		Adults		Elderly	
Eff. Class	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent
<0.21	67	5.29	18	4.49	38	5.09	11	9.24
0.21-0.40	265	20.92	91	22.69	149	19.95	25	21.01
0.41-0.60	479	37.81	161	40.15	269	36.01	49	41.18
0.61-0.80	327	25.81	97	24.19	202	27.04	28	23.53
0.81-1.00	129	10.18	34	8.48	89	11.91	6	5.04
Total	1,267	100	401	100	747	100	119	100
Mean	0.54		0.52		0.55		0.49	
Std deviation	0.20		0.19		0.21		0.19	
Min	0.01		0.02		0.01		0.01	
Max	0.97		0.97		0.97		0.93	

Youth=18-35 years; Adult=36-60 Years; Elderly>60 years.

In a similar connection, technical efficiency of youths, adults and the elderly were 0.52, 0.55 and 0.49, respectively as shown in Table 8, indicating that pearl millet farmers aged between 36-60 years (adults) were more technically efficient than youths (18-35 years) and the elderly (above 60 years). Youths, adult and elderly engaged in pearl millet farming can still improve their technical efficiencies by about 48%, 45% and 51%, respectively. In other words, there is enormous potentials in pearl millet farming across all age groups based on availability and access to production inputs. The mean efficiency of youths reported here is lower than the one reported in Ondo state, estimated to be 0.85 [69]. However, this is close to the 49% TE reported by [70] from Ghana.

4.3. Cost Elasticities and Economies of Scale

Results of the parametric analysis of the cost of production of pearl millet farming presented in Table 9 and Table 10 show that the assumption of AI was rejected at 1% level of probability. Though half-normal translog SFCF provided a better fit than the exponential and truncated translog SFC function, the SUREG and the cost system, it was not an increasing function of prices of inputs. The most appropriate model is the translog PCS which is both stable and efficient [22]. The translog functional form found to be a better representation of production technology than the CD in crop farming when modelling cost function [37,71]. The null hypothesis that adopters and non-adopters had the same cost function was rejected at 1% level of probability (LR = 309.51; p<0.001).

The implication is that the total cost of pearl millet production responded differently to changes in input prices between adopters and non-adopters. The estimate of the Wald statistic for the pooled (Wald =6,758.03, p<0.01), adopters (Wald =6,758.03, p<0.01) and non-adopters (Wald =6,758.03, p<0.01) were significant, implying that the models are relevant in explaining the relationship between total cost and input prices (Table 10). In other words, all the input prices and pearl millet output jointly determine the cost of production. The estimates of the cost elasticities and economy of scale were subsequently considered to facilitate the interpretation of the results.

The output cost elasticity for adopters and non-adopters were -0.382 and -0.476, respectively (Table 11) signifying that there was an indirect relationship between cost of production and quantity of pearl millet produced such that a 10%t increase in output would result in a reduction in cost of production by 4% and 5% among adopters and non-adopters, respectively. The cost of production among adopters and non-adopters would virtually have the same response to output changes. The cost elasticity of price of land, seeds and fertilizer were all positive and significant, therefore consistent with *a priori* expectations. In other words, increase in input prices would lead to increases in cost of production. If the price of improved seeds, for example increases by 10%, the cost of production among adopters and non-adopters would increase by 3.2% and 3.4%, respectively. Similarly, if the price of fertilizer increases by 10%, the cost of production would also increase by about 2% and 2.2% among and adopters and non-adopters, respectively. These findings indicate that the cost of production of pearl millet is inelastic to changes in output and input prices. The estimate of SCE for adopters and non-adopters was 1.38 and 1.48, which were positive implying that large-scale pearl millet producers could be more efficient [45]. In other words, increasing the scale of production will be beneficial to cost reductions.

Table 9. Likelihood ratio test for specification of cost function

Test	Null hypothesis	LR	Critical value	*p*-value
1	OLS Cobb-Douglas Vs OLS translog	206.59	28.86	<0.001
2	OLS translog Vs Expon. translog	75.87	9.50	<0.001
3	OLS translog Vs Half-normal translog	48.84	9.50	<0.001
4	OLS translog Vs Truncated translog	75.83	12.81	<0.001
5	SF Expon. translog Vs Half-normal translog	-27.03	0.46	>0.1
6	Half-normal. translog Vs Truncated translog	26.99	12.81	<0.001
7	SUREG Vs Half-normal. translog	15,967.56	37	<0.001
8	Cost System Vs Half-normal. translog	15,685.13	49	<0.001
9	Adopters and Nonadopters	309.51		<0.001

Table 10. Maximum likelihood estimates of partially correlated cost system

Variable	Parameter	Pooled	Adopters	Nonadopters
Constant	α_0	8.666 (0.477)***	6.195 (1.111)***	4.730 (0.484)***
Output	α_y	-0.316 (0.131)**	-0.806 (0.325)**	-0.232 (0.140)*
Price of land	α_1	-0.458 (0.026)***	-0.044 (0.043)	0.423 (0.032)***
Price of seed	α_2	0.471 (0.034)***	0.043 (0.06)	-0.462 (0.037)***
Price of fertilizer	α_3	0.798 (0.014)***	1.05 (0.051)***	1.137 (0.025)***
Output squared	α_{yy}	0.004 (0.019)	0.059 (0.048)	-0.023 (0.021)
Price of land squared	α_{11}	0.176 (0.003)***	0.07 (0.008)***	0.081 (0.007)***
Price of seed squared	α_{22}	0.048 (0.005)***	0.149 (0.014)***	0.089 (0.013)***
Price of fertilizer squared	α_{33}	0.068 (0.00)***	-0.121 (0.010)***	-0.139 (0.004)***
Price of land*Price seed	α_{12}	-0.068 (0.004)***	-0.143 (0.010)***	-0.111 (0.009)***
Price of land*Price of fert.	α_{13}	-0.095 (0.002)***	0.13 (0.007)***	0.063 (0.005)***
Price of seed*Price of fert	α_{23}	0.003 (0.002)	-0.007 (0.009)	0.047 (0.005)***
Output*Price of land	α_{y1}	-0.023 (0.002)***	-0.011 (0.005)**	-0.028 (0.003)***
Output*Price of seed	α_{y2}	0.036 (0.003)***	0.018 (0.007)***	0.065 (0.005)***
Output*Price of fert	α_{y3}	-0.01 (0.001)***	0.003 (0.005)	-0.013 (0.002)***
Usigmas	σ	-2.269 (0.499)***	-0.996 (0.262)***	-1.841 (0.244)***
Cov(s1,s1)	s11	-0.776 (0.048)***	-1.063 (0.122)***	-0.875 (0.043)***
Cov(s2,s2)	s22	-2.65 (0.020)***	-2.554 (0.05)***	-2.236 (0.025)***
Cov(s3,s3)	s33	-3.15 (0.020)***	-3.38 (0.087)***	-3.094 (0.025)***
Cov(s4,s4)	s44	-5.054 (0.020)***	-3.272 (0.083)***	-3.639 (0.026)***
Cov(s3,s3)	s32	-0.088 (0.002)***	-0.111 (0.006)***	-0.138 (0.004)***
Cov(s4,s2)	s42	0.016 (0.001)***	0.042 (0.006)***	0.039 (0.002)***
Cov(s4,s3)	s43	-0.034 (0.001)***	-0.053 (0.005)***	-0.029 (0.001)***
Log-likelihood function		7423.49	1091.250	4063.86***
Wald chi2(35)		210.77***	122.76***	511.29***
Number of observations		1267	258.00	1009

***<0.01, **<0.05, and *<0.1; () Standard errors in brackets; prices and output are in natural logarithm; Estimates of the share equations are not reported but can be provided upon request.

Table 11. Estimates of cost elasticities on input prices and returns to scale

Variable	Param.	Pooled	Adopters	Nonadopters
Price of output	e_y	-0.463 (0.015)***	-0.382 (0.032)***	-0.476 (0.016)***
Price of land	e_{x1}	0.443 (0.002)***	0.460 (0.005)***	0.464 (0.003)***
Price of seed	e_{x2}	0.309 (0.003)***	0.317 (0.007)***	0.339 (0.005)***
Price of fert.	e_{x3}	0.216 (0.001)***	0.195 (0.005)***	0.219 (0.002)***
Scale Economy	SCE = $(1-e_y)$	1.46	1.38	1.48

***<0.01; () Standard errors in brackets.

4.4. Allocative Efficiency (AE)

The distribution of the AE between adopters and non-adopters shows that pearl millet farming was cost efficient (Table 12). The mean AE of adopters and non-adopters, for example, was 0.74 and 0.70, respectively, implying that 74% and 70% of the expected cost was achieved by adopters and non-adopters, respectively. In other words, 26% and 30% of excess cost was incurred by adopters and non-adopters, respectively, due to AI. These results agree with those of [18] who found that AE in millet-based farming system ranges from 0.55 to 0.96 in the derived Savanna zone of Nigeria. The distribution of respondent across inefficiency classes indicates that most respondents had more than 60% AE. Among adopters, the least cost-efficient respondents realized 35% of expected minimum cost while non-adopters attained 56%. This point to the fact that the least cost-efficient adopter and non-adopter can still reduce cost of production by 65% 44%, respectively, and still produce existing output level. Also, adopters were more efficient than non-adopters with a difference of barely 4%.

Both male and female pearl millet respondents practically had the same level of AE, though male adopters were more efficient than female adopters (Table 13). Literature provides mixed results on male-female PE differentials. In controlling for endogeneity of factors of production, [38] revealed that female farmers were less efficient than male farmers in allocating production inputs. In the case of northern Nigeria, the socio-cultural context favours men to be more exposed to agricultural technology promotional events such as trainings, field days, exchange visits, demonstrations, etc. However, neither male nor female farmers had absolute AE signifying that there is still room for reducing cost of production among farmers of both sexes. The level of AE was more or less the same across the states. Among female farmers, Katsina state (0.71) was the least efficient state in input allocation while Yobe state was the least. Male farmers in Jigawa state were the most efficient resource in resource allocation (0.73) which is also the most efficient in the pooled results followed by Kano and Katsina states with AE of 0.72 each. AI could be a function of market failure manifested in the form of price instability and differentials across the states [32].

Table 12. Descriptive statistics of allocative efficiency based on adoption status

	Pooled		Adopters		Non-adopters	
Eff. class	Freq	Percent	Freq	Percent	Freq	Percent
<0.40	1	0.08	1	0.39	0	0
0.41-0.60	42	3.31	29	11.24	13	1.29
0.61-0.80	1,130	89.19	143	55.43	987	97.82
0.81-1.00	94	7.42	85	32.95	9	0.89
Total	1,267	100	258	100	1,009	100
Mean	0.71		0.74		0.70	
Std deviation	0.07		0.12		0.04	
Min	0.35		0.35		0.56	
Max	1.00		1.00		0.81	

AD=Adopters; Nona=Nonadopters.

Table 13. Estimates of allocative efficiency based on sex and adoption status

	Women			Men			Pooled		
State	Pooled	AD	Nona	Pooled	AD	Nona	Pooled	AD	Nona
Bauchi	0.70	0.00	0.70	0.71	0.73	0.71	0.71	0.73	0.71
Jigawa	0.69	0.72	0.69	0.73	0.75	0.71	0.73	0.75	0.71
Kano	0.69	0.66	0.70	0.72	0.75	0.70	0.72	0.75	0.70
Katsina	0.71	0.71	0.71	0.72	0.77	0.70	0.72	0.77	0.70
Kebbi	0.70	0.63	0.71	0.70	0.69	0.71	0.70	0.68	0.71
Sokoto	0.70	0.00	0.70	0.70	0.69	0.70	0.70	0.69	0.70
Yobe	0.68	0.00	0.68	0.70	0.71	0.70	0.70	0.71	0.70
Total	0.70	0.69	0.70	0.71	0.74	0.70	0.71	0.74	0.70

AD=Adopters; Nona=Nonadopters.

Table 14. Descriptive statistics of allocative efficiency based on age-groups

	Pooled		Youths		Adults		Elderly	
Eff. class	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent
<0.21	0	0	0	0	0	0	0	0
0.21-0.40	1	0.08	1	0.25	0	0	0	0
0.41-0.60	42	3.31	13	3.24	24	3.21	5	4.2
0.61-0.80	1,130	89.19	359	89.53	660	88.35	111	93.28
0.81-1.00	94	7.42	28	6.98	63	8.43	3	2.52
Total	1,267	100	401	100	747	100	119	100
Mean	0.71		0.71		0.71		0.70	
Std deviation	0.07		0.06		0.07		0.06	
Min	0.35		0.35		0.41		0.53	
Max	1.00		0.90		1.00		0.95	

As demonstrated in Table 14, the level of AE was about the same between youths, adults and the elderly (0.71) implying that 29% of cost can still be reduced while maintaining yield performance of 1,212 kg/ha and 1,068 kg/ha among adopters and non-adopters, respectively. Although youths are usually keen to adopt improved technologies, their lack of experience in farming could be a setback in AE.

4..5. Economic Efficiency (EE)

Minimum and maximum EE was 0.01 and 0.88, respectively, implying that there were important variabilities in EE among the respondents (Table 15). EE of adopters (36%) was between 0.41- 0.60, and ranged between 0.21 - 0.40 for 48% of non-adopters. Mean EE of adopters and non-adopters was 0.52 and 0.43, respectively, implying that adopters and non-adopters were 43% and 37% economically efficient, respectively. Overall efficiency in pearl millet production can still be improved substantially with AI being the major source of shortfall. The finding is in line with [18] who found that there are potentials for improving EE in cassava-based farm production systems in the derived Savanna zone of Nigeria. Analysis by sex showed that the EE of men (0.38) was slightly greater than that of women (0.36). Though male adopters were economically more efficient (0.44) than female non-adopters (0.34), economic efficiency of male non-adopters (0.37) was the same like that of female non-adopters (0.36). This finding further suggests that adoption of improved millet varieties contributed in improving the performance of adopters.

Table 15. Descriptive statistics of economic efficiency based on adoption status

	Pooled		Adopters		Non-adopters	
Eff. class	Freq	Percent	Freq	Percent	Freq	Percent
<0.21	152	12	26	10.08	126	12.49
0.21-0.40	577	45.54	89	34.5	488	48.36
0.41-0.60	450	35.52	92	35.66	358	35.48
0.61-0.80	83	6.55	46	17.83	37	3.67
0.81-1.00	5	0.39	5	1.94	0	0
Total	1,267	100	258	100	1,009	100
Mean	0.38		0.43		0.37	
Std deviation	0.15		0.19		0.13	
Min	0.01		0.01		0.01	
Max	0.88		0.88		0.76	

AD=Adopters; Nona=Nonadopters.

Table 16. Estimates of economic efficiency based on sex

	Female			Male			Pooled		
State	Pooled	AD	Nona	Pooled	AD	Nona	Pooled	AD	Nona
Bauchi	0.35	0.00	0.35	0.39	0.42	0.38	0.38	0.42	0.37
Jigawa	0.37	0.28	0.39	0.42	0.46	0.37	0.41	0.46	0.37
Kano	0.35	0.26	0.37	0.39	0.43	0.37	0.39	0.42	0.37
Katsina	0.41	0.42	0.40	0.38	0.43	0.36	0.38	0.43	0.36
Kebbi	0.36	0.47	0.36	0.36	0.41	0.36	0.36	0.41	0.36
Sokoto	0.38	0.00	0.38	0.37	0.39	0.37	0.37	0.39	0.37
Yobe	0.32	0.00	0.32	0.37	0.43	0.37	0.37	0.43	0.36
Total	0.36	0.34	0.36	0.38	0.44	0.37	0.38	0.43	0.37

AD=Adopters; Nona=Nonadopters.

Table 17. Descriptive statistics of economic efficiency based on adoption status

	Pooled		Youth		Adult		Elderly	
Eff. class	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent
<0.21	152	12	51	12.72	80	10.71	21	17.65
0.21-0.40	577	45.54	192	47.88	328	43.91	57	47.9
0.41-0.60	450	35.52	136	33.92	279	37.35	35	29.41
0.61-0.80	83	6.55	21	5.24	56	7.5	6	5.04
0.81-1.00	5	0.39	1	0.25	4	0.54	0	0
Total	1,267	100	401	100	747	100	119	100
Mean	0.38		0.37		0.39		0.34	
Std deviation	0.15		0.14		0.15		0.14	
Min	0.01		0.01		0.01		0.01	
Max	0.88		0.88		0.88		0.69	

Table 17 shows that the level of AE was about the same for youths, adults and elderly (0.71). This finding indicate that youths, adults and elderly pearl millet farmers operated far below potential profit levels. The overall low efficiency of youths is in agreement with the fact youths generally have limited access to capital that may restrict them from using improved technologies [72].

5. Conclusion and Recommendations

The use of the translog PCS approach helped in the identification of parameters with more precision than the classical single equation stochastic frontier translog function. Estimates of PE in pearl millet farming in this study highlighted differences between adopters and non-adopters and disaggregated outcomes by sex, age-groups and states using the approach. Outcomes of the analysis show that production levels of pearl millet and cost of production can substantially be improved through the reduction of technical and allocative inefficiencies. AI was the major source of production inefficiency highlighting the importance of addressing input price instability and limited access to credit facilities. Adopters were more efficient than non-adopters, although the difference had no causal interpretation considering that both groups were in the same geographic location. Adults had a higher efficiency than youths and the elderly. The study recommends more efforts to be directed at developing knowledge and skills of both extension agents and farmers to ensure that farmers better understand crop varieties and recommended crop management practices. Also, access to adequate farm land and credit will encourage farmers to improve the scale of production that will enable them take advantage of economies of scale.

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