

# A Framework for Determining the Impact of Value Chain Participation on Smallholder Farm Efficiency

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## Abstract

We analyze the efficiency of wheat farmers toward the ever-increasing demand for wheat in Tanzania. Translog production and cost functions were utilized in the stochastic frontier analysis to examine technical, allocative, and economic efficiencies (TE, AE, and EE) of wheat farmers in Northern Tanzania. Propensity score matching through caliper radius and nearest neighbor methods were utilized to analyze the impact of value chain participation on smallholder farm efficiency levels. Analysis revealed that the average TE, AE, and EE scores for farmers' value chain participation were 79%, 80%, and 64%, respectively, in the study area, implying that wheat farmers could still improve level of TE, AE, and EE by 21%, 20%, and 36%, respectively. Caliper radius matching revealed that the net effects of farmers' participation in vertical coordination on TE, AE, and EE were 6.8%, 5.7%, and 8.7%, respectively, while the net effects of farmers' horizontal coordination participation were 6.3%, 9.5%, and 11.6%, respectively. This indicates that farmer's participation in value chain (vertical and horizontal coordination) would positively impact their level of wheat farm efficiencies. Based on the results, we recommend the expansion of wheat plots and use of modern farming technologies to increase wheat production in Tanzania. To further improve farm unit efficiency, we recommend additional formal education for future farmers, more on-farm extension training, and participation in the value chain through contracts and farmers' associations.

## Keywords

Efficiency, Wheat, Tanzania, Propensity Score Matching, Stochastic Frontier Analysis

## 1. Introduction

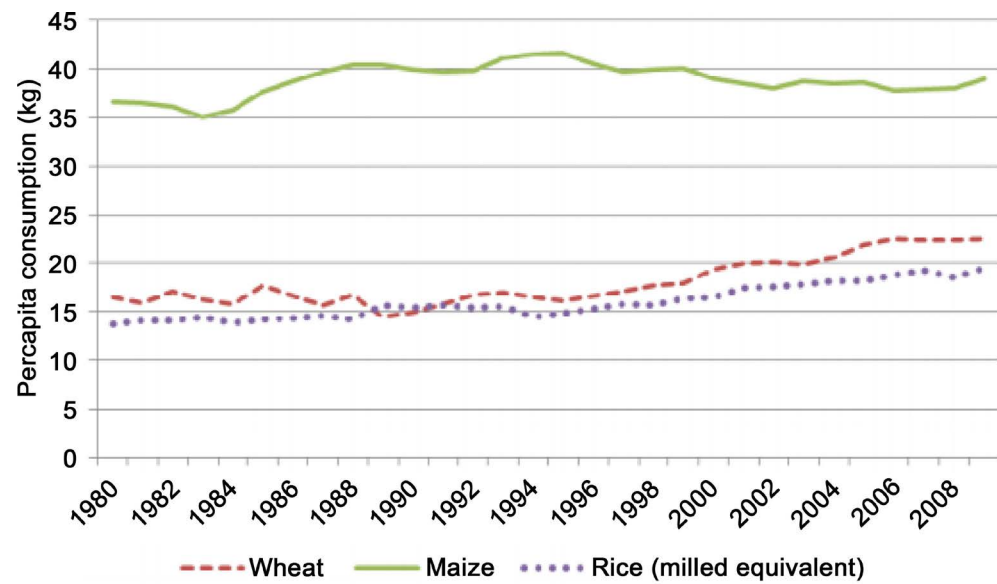
Demand for wheat in Tanzania has risen considerably since 2000. Several factors have contributed to the rise in wheat demand, including increasing population, rapid urbanization, rising incomes, and changes in food preferences toward wheat and wheat products. Despite the relative abundance of suitable land for wheat production in Tanzania, domestic production has lagged considerably behind demand, leading to a heavy reliance on imports to satisfy domestic demand. This untenable situation is draining the Tanzanian economy of valuable foreign exchange that could otherwise be deployed for other types of economic development.

To meet the emerging demand and food preference for wheat products in Tanzania, the marketing literature suggests coordination between the various business actors [1] [2]. Increased coordination of vertical and horizontal value chains is likely to impact farm efficiency and production levels. While other studies have focused on the coordination effect on productivity [3] [4] [5], we focus on the impact of value chain participation on smallholder farm efficiency levels.

Participation in the value chain (PVC) could impact farmers' technical, allocative, and economic efficiencies (TE, AE, and EE) in several ways. For one, PVC could affect farmers' choice of factors of production, especially when the post-harvest value chain actors have strict requirements regarding product quantity and quality. For example, the minimum volume of output required may cause farmers to expand their farm operations and employ improved technologies such as hybrid seeds, fertilizers, pesticides, herbicides, and irrigation systems. PVC influences TE and AE because it facilitates access to factors of production, prices, and markets for the crop of interest.

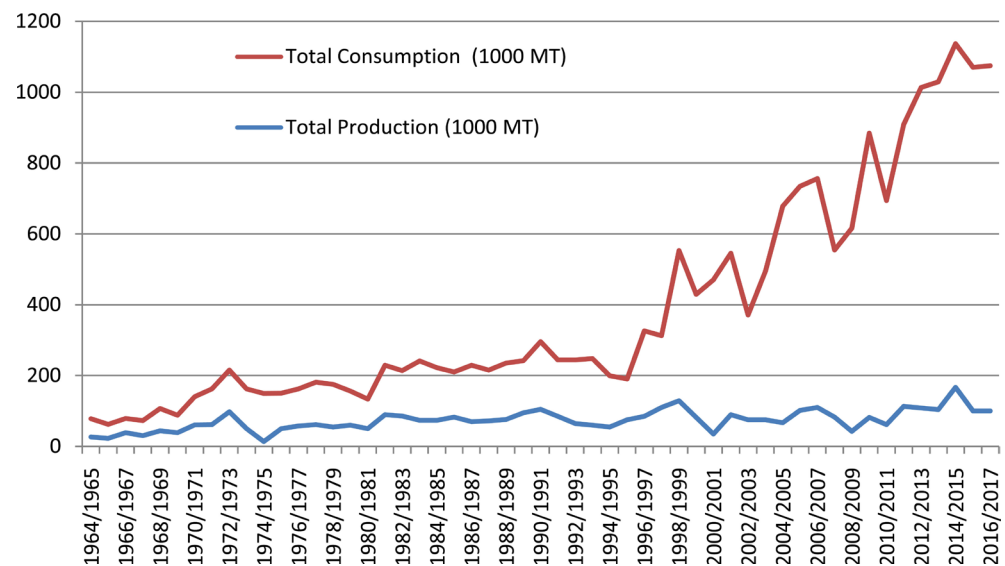
We focus on wheat as the crop of interest for several reasons. The growth in per capita consumption of wheat has outstripped that of maize and rice which are staple foods in Tanzania. Between 1990 and 2010, annual per capita consumption of wheat, maize, and rice increased by 0.35 kg, 0.3 kg, and 0.32 kg, respectively [6]. **Figure 1** depicts the trends in per capita consumption of wheat, maize, and rice for Sub-Saharan Africa (SSA) over the period 1998 to 2008 (the latest year for which data are available). These trends typify the situation in Tanzania, where the gap between the per capita consumption of maize and wheat has narrowed. **Figure 2** shows wheat consumption and production trends from 1964/65 to 2016/17 in Tanzania, with a noticeable sharp increase in the per capita consumption gap occurring from 1997 to 2016 lagging behind domestic production.

Although Tanzania has the potential to increase its production of wheat, improving the level of production presents several challenges, notably expensive inputs (chemicals, seeds, and fertilizers); insufficient farm machinery; high fuel prices; unstable crop prices; and the subdivision of large-scale farms into smaller units [7]. Small-scale farmers in Tanzania, who represent a large share of the wheat producers, differ significantly from large-scale farmers in their use of in-



Source: Mason et al. (2012 [6]).

**Figure 1.** Per capita consumption gap between wheat and staple foods (maize and rice) in SSA.



**Figure 2.** Production and consumption trends of wheat in Tanzania. 1964/65-2016/17.

puts, agronomic practices, and productivity. Seventy percent of small-scale farmers in Tanzania use hand tools to plow their fields compared to 20% utilizing more modern technology such as tractors and machine-operated threshers. Fertilizer usage by small-scale farmers is very low at only 15% [8].

Bringing about a noticeable increase in wheat production and farm efficiency may require the expansion of production plots and access to modern technologies. Since there are scarce resources for wheat cultivation in Tanzania, determining the efficiency and understanding how this efficiency may be impacted by value chain participation will be crucial in taking advantage of wheat marketing opportunities. The results of such an analysis will provide critical information to form policies that will lead to improvements in an enabling environment.

We use the stochastic frontier and propensity score matching (PSM) approaches to estimate the impact of participation in the value chain on TE, AE, and EE of wheat farmers in Tanzania. PSM is used to account for selection biases on the value chain participation. The study is in line with the policies espoused by the Government of Tanzania for food self-sufficiency, rural employment creation, and poverty reduction through agricultural productivity. We contribute to the current academic literature by combining two approaches of SFA and PSM to address one study question on wheat farm efficiency. Furthermore, we are the first to study production efficiencies comprehensively regarding wheat producers in Tanzania and the role of value chain participation on production efficiencies of Tanzania producers. Improving the efficiency would significantly help reduce the demand for imported wheat, increase Tanzania' wheat farmer income, and reduce foreign currency spent on wheat import.

This paper is organized into six sections where the first section covers background information, the study question addressed, a brief of the model used for analysis, and significance of the study. The second part describes the theoretical model while the third section detailed the empirical model specified for analysis. The fourth section describes the data used in the analysis followed by the results and discussion in the fifth section. The last section provides the conclusion and recommendations for future study.

## 2. Theoretical Model

The efficiency of firms/farms is measured either by parametric or nonparametric approaches. The parametric and non-parametric approaches employ econometric and mathematical techniques, respectively. Under parametric approach the stochastic frontier analysis (SFA) is commonly used while nonparametric approach uses data envelop analysis (DEA). DEA assumes that the deviations from production frontier are the outcome of inefficiencies, no noise or measurement errors are considered while SFA considers noise or measurement errors by assuming a functional form that underlies a certain technology. By this assumption, parametric approaches derive parameters for the model that depends on the specification of the production function that fits to the data. SFA is mostly used in parametric specification because of its capability of separating inefficiency and random noise effects from composite error. With that regards, this study opts parametric frontier models over nonparametric.

In studies dealing with efficiency, the production frontier approach is used to estimate the production function, the dual cost function, and the profit function [9]. These estimations in turn provide a measure of i) the maximum production yield to be achieved given a set of input requirements; ii) the minimum cost of production given the prices of the input requirements; and iii) the maximum profit possible given the inputs requirements, the outputs produced, and the prices of input and output. In this context, the purpose of developing production, cost, or profit models is to obtain one or more measures of efficiency by allowing for deviations of observed choices from optimal ones. These deviations are mod-

eled as statistical errors. Technical inefficiency arises when, given the chosen inputs, output falls short of the ideal. In terms of costs, inefficiency can originate from two sources: technical or allocative inefficiency. The latter relates to suboptimal input choices given input prices. Economic inefficiency is the blend of the two previously mentioned inefficiency measures. We use this framework to analyze the TE, AE, and EE of wheat farmers in Tanzania as described below.

The stochastic frontier function can incorporate a composite error term and a one-sided error term. The composite error term captures a random effect that arises outside the control of a firm (farmer) while the one-sided error term represents an inefficiency component of the production unit [10].

Generally, the multiplicative production frontier is modeled as

$$Q = f(x; \beta) e^v e^{-u} \quad (1)$$

where  $Q$  is the firm's output,  $x$  is the firm's inputs used for production,  $\beta$  is the unknown vector of parameters to be estimated,  $e$  is the exponent term,  $v$  is the stochastic error, and  $u$  represents the inefficiency term. The terms  $v$  and  $u$  are independently and identically distributed with variances  $\sigma_v^2$  and  $\sigma_u^2$ , respectively. The stochastic effect  $v$  is outside farmers' control due to factors such as rainfall, temperature, and natural disasters. These factors are measurement errors and are unobservable statistical noises. Following Pitt and Lee [11] and Jondrow *et al.* [10]  $v$  is assumed to be normally distributed as  $v \sim N(0, \sigma_v^2)$  while  $u$  is half normally distributed as  $u \sim N_+(0, \sigma_u^2)$  and reflects technical inefficiency. Equation (1) above can be transformed into a logarithm as

$$\log Q = \log f(x; \beta) + v - u.$$

The transformed Equation (2) can now be used to estimate  $\beta$ ,  $\lambda$ , and  $\sigma^2$  by applying the maximum likelihood (ML) method,

$$l(\beta, \sigma^2, \lambda) = -\frac{1}{2} N \log \left( \frac{\pi}{2} \right) - \frac{1}{2} N \log \sigma^2 + \sum_{N=1}^N \log \Phi \left( -\frac{\lambda \varepsilon_N}{\sqrt{\sigma^2}} \right) - \frac{1}{2\sigma^2} \sum_{N=1}^N \varepsilon_N^2, \quad (2)$$

where  $\varepsilon = Q - f(x; \beta)$ , and  $\beta$ ,  $\sigma^2$ , and  $\lambda$  are estimated by the stochastic frontier model using the maximum likelihood method. The R package (SFA) from *Benchmarking* is used to conduct the analysis [12].

Conversely, the cost functions show the minimum cost of producing the output  $Q$  when the input prices  $r$  and the technology set  $T$  are given as follows:

$$c(r, Q) = \min_x \{rx \mid (x, Q) \in T\}. \quad (3)$$

The above formula explains that the observed cost is higher than or equal to the optimized cost. That is,

$$rx \geq c(r, Q), \quad \forall (x, Q) \in T. \quad (4)$$

Therefore, the cost efficiency which is the ratio of the optimized cost to the observed cost is given by

$$CE = \frac{c(r, Q)}{rx}. \quad (5)$$

Thus,

$$CE \leq 1 \quad \text{for } (x, Q) \in T. \quad (6)$$

As in the production function, we can express cost efficiency by using  $u$  which becomes

$$CE = \exp(-u) \quad (7)$$

where  $u \leq 0$  when  $CE \leq 1$  for  $(x, Q) \in T$ .

By introducing the multiplicative expression of error term  $v$ , the cost efficiency can now be expressed as

$$CE = \frac{c(r, Q)\exp(v)}{rx} \quad (8)$$

$$rx = C = \frac{c(r, Q)\exp(v)}{CE} = \frac{c(r, Q)\exp(v)}{\exp(-u)} = c(r, Q)\exp(v)\exp(u). \quad (9)$$

Thus,

$$C = c(r, \alpha, Q; \alpha)\exp(v)\exp(u). \quad (10)$$

Given that Equation 10 is similar to Equation (1), the estimation procedures following MLE are the same.

## 2.1. Technical, Allocative, and Economic Efficiency

After completing the theoretical procedures to estimate the SFA parameters and to decompose the error term into noise and inefficiency, the firm-specific level of efficiency can be estimated. The firm-specific efficiency by Shephard's lemma is obtained from the ratio of the observed output to the maximum output or its inverse (Farrell approach) that can be produced with the observed input quantities. Accordingly, the technical efficiency is given by

$$TE = \frac{f(x; \beta)\exp(-u)}{f(x; \beta)} = \exp(-u). \quad (11)$$

Since  $u$  is not observed in the SFA analysis, the approach outlined by Bogtoft and Otto [13] is used to obtain this value. Specifically, Bogtoft and Otto show that  $u$  can be manually calculated with some estimated parameters from the SFA as follows:

$$u = -\varepsilon \frac{\sigma_u^2}{\sigma^2} = -\varepsilon \frac{\lambda^2}{1 + \lambda^2} = -\varepsilon\gamma \quad (12)$$

where the variables in the equation are as defined by Equation (2).

AE represents the least cost combination of inputs to obtain the maximum level of revenue. When output  $Q$  and input price  $r$  are known, the dual cost function which can be used to measure AE and TE is expressed as a function of input prices ( $r$ ) and output ( $Q$ ). The extra advantage of the dual cost function is that it can provide answers that are also provided by the production function by applying Shephard's lemma which states that if the dual cost function is

convex, then the cost minimizing point of a given good with a given price is unique:

$$CE = \frac{c(r, Q) \exp(v)}{rx}. \quad (13)$$

## 2.2. Determining Factors Influencing Efficiency

Bravo-Ureta and Rieger [14] noted that, within the literature, several researchers have conducted studies relating to efficiency for various socioeconomic variables by focusing on two approaches. One approach uses correlation coefficients to conduct a simple nonparametric analysis. The second approach uses a two-step procedure to estimate the farm efficiency level before regressing the efficiency scores on possible socioeconomic attributes. We chose the second approach using the censored Tobit regression model where the lower and upper limit of the observed dependent variable can take any value. Since our efficiency scores are bounded between 0 and 1, the approach proposed by Henningsen [15] is used and is described as follows:

$$u_i^* = K'\alpha + \varepsilon_i \quad (14)$$

$$u_i = \begin{cases} a & \text{if } u_i^* < a \\ u_i^* & \text{if } a < u_i^* < b \\ b & \text{if } u_i^* \geq b \end{cases} \quad (15)$$

where  $u$  represent the efficiency scores,  $K$  are the factors believed to influence efficiency levels,  $a$  is the minimum efficiency level, and  $b$  is the maximum efficiency level. Censored regression models are usually estimated by maximum likelihood (ML). Assuming that the disturbance term  $\varepsilon$  follows a normal distribution with mean 0 and variance  $\sigma^2$ , the log-likelihood function is

$$\begin{aligned} \log L = \sum_{i=1}^N & \left[ I_i^a \log \Phi \left( \frac{a - x_i' \delta}{\sigma} \right) + I_i^b \log \Phi \left( \frac{x_i' \delta - b}{\sigma} \right) \right. \\ & \left. + (1 - I_i^a - I_i^b) \left( \log \varnothing \left( \frac{u_i - x_i' \delta}{\sigma} \right) - \log \sigma \right) \right] \end{aligned} \quad (16)$$

where  $\varnothing(\cdot)$  and  $\Phi(\cdot)$  denote the probability density function and the cumulative distribution function, respectively, of the standard normal distribution, and  $I_i^a$  and  $I_i^b$  are indicator functions with

$$I_i^a = \begin{cases} 1 & \text{if } u_i = a \\ 0 & \text{if } u_i > a \end{cases} \quad (17)$$

$$I_i^b = \begin{cases} 1 & \text{if } u_i = b \\ 0 & \text{if } u_i < b \end{cases}. \quad (18)$$

The log-likelihood function of the censored regression model (equation 16) can be maximized on the parameter vector  $(\delta', \sigma)'$  using standard non-linear optimization algorithms. The ‘‘cens Reg’’ package from the R software was used to estimate the model [16].

### 2.3. Value Chain Participation Effect on Efficiencies: Bias Selection

The stochastic frontier approach marks the differences in TE, AE, and EE for each firm (farmer) considered in the analysis, as do the groups of participants and nonparticipants in the value chain. Due to selection bias (self-selection), propensity score matching would be appropriate in stochastic frontier analysis [17].

The literature has considered various matching procedures for covariates but the most common ones used are Nearest Neighbor matching, Caliper radius matching, Kernel matching, Mahalanobis matching, and Stratified radius matching [18]. We employ nearest neighbor and caliper radius matching to generate an unbiased sample for analysis. Nearest Neighbor Matching pairs the participants and nonparticipants of the value chain who are closest in terms of probability of participation  $P(z)$  as identical partners. Conversely, caliper radius matching uses a radius distance in which all the control units falling within the radius are matched to the treated unit in order to construct a counterfactual outcome. That is, the outcome for nonparticipants is matched with the outcome for participants, and the difference is the effect of the program for each participant. The average difference for all matched samples is the estimate of the average treatment effect on the treated (ATT), or the net impact of the program.

One drawback of PSM is that it can only control for observable characteristics which means there could still be a selection bias due to unobservable factors [19]. We assume that the distribution of unobservables is the same for participants and nonparticipants. Accordingly, Rosenbaum [20] proposed the standard bounding test to evaluate how strongly the unobservables could influence the selection bias to nullify the implication of the matching process.

Few studies have used a combined SFA and PSM approach in assessing the impact of programs. Bravo-Ureta *et al.* [21] used the stochastic frontier framework and PSM approach for evaluating TE between the beneficiaries and non-beneficiaries of the MERANA program in Honduras. By controlling both the observable and unobservable selection bias using PSM and the selection correction model proposed by Greene [9], they found that the mean TE was higher for the treated group than for the control group and that the hypothesis of the presence of selectivity bias could not be rejected. They further found that the treated group performed well in both TE and frontier output. However, their study applied only nearest neighbor matching without replacement and was silent on the extent to which ATT would improve, opting only to give the ranges. Abate *et al.* [22] applied PSM to compare the TE of cooperative farmers and independent farmers in Ethiopia using the kernel regression method. Their study found that the hidden selectivity bias was insensitive to the analysis and that participation in agricultural cooperatives improved farmers' efficiencies.

Unlike Mayen *et al.* [17], we used PSM after estimation, rather than before, to avoid losing observations for the frontiers analysis. First, we used PSM to match the covariates of the farm and farmer characteristics rather than simply com-



paring the outcome variables (TE, AE, and EE) between the participants and nonparticipants of the value chain. Then we used PSM to match the outcomes between the participants (treated) and nonparticipants (control) of the value chain that are similar in terms of observable features. This match closed the bias gap to some extent that would exist when the two clusters are systematically different [23].

PSM involves three stages. In the first stage, the propensity scores (predicted probabilities,  $P(z)$ ) are generated from a logit or probit model that gives the probability of a farmer participating in the value chain. In the second stage, the control group (nonparticipants) is constructed by matching their propensity scores with those of the treated group that were generated from logit or probit models. The treated group (participants) with no good matches and the control group (nonparticipants) not used in the matching are dropped from the analysis. In the third stage, the ATT is calculated for the outcomes (TE, AE, and EE). ATT is the outcome difference between the two groups (treated and untreated) where their covariates are matched and balanced by the propensity scores.

### 3. Empirical Model

#### 3.1. Technical Efficiency

We employ one of the flexible functional forms of translog production to estimate the production frontier (Equation (1)) because it allows variations in elasticity. Thus, this equation is specified as

$$\ln(Q_j) = \alpha_0 + \sum_{i=1}^5 \alpha_i \ln X_i + \frac{1}{2} \sum_{i=1}^5 \sum_{k=1}^5 \alpha_{ik} \ln X_i \ln X_k + (v_j - u_j) \quad (19)$$

where

- $Q$  = Quantity of wheat produced in kg,
- $X_1$  = Size of wheat plot in acres,
- $X_2$  = Amount of fertilizer applied in kg/acre,
- $X_3$  = Amount of chemicals (herbicides, insecticides, pesticides) applied in Lt/acre,
- $X_4$  = Labor used in man-days,
- $X_5$  = Amount of local/hybrid seed planted in kg/acre,
- $\alpha_0, \alpha_1 \dots \alpha_5$  = unknown parameters to be estimated,
- $v_j$  = noise or disturbance follows normal distribution  $N(0, \sigma_v^2)$ ,
- $u_j$  = technical inefficiency which is positive and half normally distributed  $N(0, \sigma_u^2)$ .

#### 3.2. Allocative Efficiency

The stochastic cost frontier is also specified as a translog cost function with a two-part error structure,  $v + u$ , where  $v$  and  $u$  are described as above. As a second order Taylor's series approximation [24], the translog cost function is expressed as the total cost of wheat production in terms of input prices and output level as follows:

$$\ln(C_j) = \alpha_0 + \sum_{i=1}^5 \alpha_i \ln r_i + \frac{1}{2} \sum_{i=1}^5 \sum_{k=1}^5 \psi_{ik} \ln r_i \ln r_k + \alpha_Q \ln Q + \frac{1}{2} \psi_{QQ} (\ln Q)^2 + \sum_{i=1}^5 \psi_{iQ} \ln r_i \ln Q + v_j + u_j \quad (20)$$

where  $j = 1 \dots N$ ,  $\psi_{ik}$  is the index of  $M$  different inputs considered and  $\psi_{ik} = \psi_{ki}$ ,  $C$  is the total cost,  $Q$  is the output, and the  $r_i$ 's are the prices of the factor inputs. For a cost function to be well behaved it must be homogeneous of degree one in prices, implying that, for a fixed level of output, total cost must increase proportionally when all prices increase proportionally. Explicitly, the conditions above are fulfilled by checking

$$\sum_{i=1}^5 \alpha_i = 1; \quad \sum_{i=1}^5 \psi_{iQ} = 0 : \text{Homogeneity.}$$

$$\sum_{i=1}^5 \psi_{ik} = \sum_{k=1}^5 \psi_{ik} = \sum_{i=1}^5 \sum_{k=1}^5 \psi_{ik} = 0 : \text{Symmetry and Homogeneity.}$$

$$\frac{\partial \ln C_j}{\partial \ln r_i} > 0, \quad \frac{\partial \ln C_j}{\partial \ln Q} > 0 : \text{Monotonicity.}$$

$\psi_{ik}$  : Hessian matrix, negative semidefinite.

The above restrictions are accomplished by normalizing the cost function by one of the input prices. While any price can be used for normalization and the analysis would result in the same parameter values, we use the labor price. The translog cost function also requires that costs be monotonically increasing and concave in input prices. Specifically, for monotonicity, the requirement is that  $\frac{\partial \ln C_j}{\partial \ln r_i} > 0$  and, for concavity, the matrix  $\psi_{ik}$  has to be negative semidefinite.

The distance from the cost frontier is measured by  $u$  [25]. Cost efficiency for the  $j^{\text{th}}$  farm is then computed as  $\exp(u_j)$ . With this formulation, cost efficiency is greater than or equal to unity. Its inverse ( $\exp(u_j)$ ) is the percentage reduction in cost necessary to bring total cost to the frontier.

The inefficiency is modeled in terms of farm-specific and household features ( $K_i$ ) as follows:

$$u_j = \alpha_0 + \alpha_i K_i + \varepsilon_i \quad (21)$$

where

$K_1$  = Contract with buyers dummy.

$K_2$  = Membership in farmers' association dummy.

$K_3$  = Age of the household head in years.

$K_4$  = Education level of the household head in years of schooling.

$K_5$  = Experience in wheat farming in years.

$K_6$  = Household composition, proportional number of people living in household.

$K_7$  = Family members aged below 18 years old in number.

$K_8$  = Family members aged between 18 years old and 50 years old in number.

$K_9$  = Family members aged above 50 years old in number.

$K_{10}$  = Rental land acquired dummy.

$K_{11}$  = Extension visits in number of times per year.

$K_{12}$  = Village and technical meetings attended in number of times per year.

$K_{13}$  = Mbulumbulu ward dummy.

- $K_{14}$  = Rhotia ward dummy.  
 $K_{15}$  = Monduli juu ward dummy.  
 $K_{16}$  = Transport ownership (car, motorcycle, oxcart) dummy.  
 $K_{17}$  = Farm equipment ownership (tractor, plow, knapsprayer, wheelbarrow) dummy.  
 $K_{18}$  = Livestock keeping dummy.  
 $K_{19}$  = Hybrid seed planted dummy.  
 $K_{20}$  = Off-farm income dummy.  
 $\alpha'$  = Parameters to be estimated.  
 $\varepsilon$  = Disturbance term.

## 4. Data

This study uses firsthand data which were collected through a field survey conducted by trained enumerators using a pre-tested questionnaire designed to study wheat farmers in northern Tanzania where 90% of the domestic wheat supply is grown [26]. Two regions, Arusha and Kilimanjaro, were chosen because they are relatively homogenous in agricultural land use, production practices, and ecological condition. Two districts from Arusha (Karatu and Monduli) and one from Kilimanjaro (Hai) were selected for the survey based on their level of wheat production. The corresponding wards were selected because wheat is grown in highland areas. The Mbulumbulu and Rhotia wards were selected in the Karatu District, the Mondulijuuward was selected in the Monduli District, and the Ngarenairobiward was selected in the Hai District to form more homogenous strata by location to represent the variability in wheat growing conditions by the wards. A combination of random and snowball sampling techniques were used to select small-scale farmers from the sampling frame provided by village officials. A structured questionnaire was used to obtain information related to production, costs, and marketing practices. Solicited background information included household size, age, gender, education, and occupation of the respondents; contracts; farmers' association memberships; and challenges farmers face when producing and marketing wheat. Opinions of key informants such as government officials and traders provided additional information that was collected along with the structured questionnaire.

Out of the 350 small-scale farmers who were sampled, including those who switched from wheat to barley production, 310 farmers completed the survey. Barley farmers were included because barley competes directly with wheat, although it sells for a slightly higher price than wheat on a unit basis and receives full support from private brewery companies. Farm land size in the survey ranged from 0.2 to 2 ha (the equivalent of 0.5 to 5 acres).

## 5. Results and Discussion

### 5.1. OLS and SFA Estimates for Translog Production and Cost Functions

Standard ordinary least squares (OLS) and maximum likelihood estimation (MLE)

of the translog production function are presented in **Table 1**. The results show that 6 of the coefficients that represent first-order derivatives are significant and have the expected signs. Land size has the expected sign, and impacts the output level in kg/acre positively at the 1% significance level. Increasing the use of insecticides decreases the level of output which is unexpected; this is significant at the 10% level for both OLS and MLE models. This outcome perhaps could be explained by inappropriate use of insecticides [27].

The second-order derivatives for all inputs are negative, implying the concavity property holds for the existing farm technology. The  $R^2$  is 95%. The  $F$  value is 147.9 and is significant at the 1% level. Lambda ( $\lambda$ ) which measures the inefficiency variation in relation to the idiosyncratic variation computed as the ratio of standard errors of  $\sigma_u$  to  $\sigma_v$  has a value of 4.003 and is significant at the 1% level. Gamma ( $\gamma$ ) which is the ratio of the efficiency variation ( $\sigma_u^2$ ) to the total variation ( $\sigma^2$ ) of parameters is 0.95. This implies that 95% of the total output variation is due to production inefficiency while 5% is due to variation from unobserved and measurement errors ( $\sigma_v^2$ ).

The translog cost frontier which is dual to the translog production frontier is shown in **Table 2**. It is econometrically estimated to provide the basis for computing both AE and EE. As mentioned earlier, the total cost and input prices were normalized by labor price per acre. The input prices included in the model are for seeds (Ps), fertilizer (Pf), herbicides (Ph), insecticides (Pi), and pesticides (Pp).

## 5.2. Efficiency Scores

TE, AE, and EE scores are reported in **Table 3**. The average TE score of the sampled wheat farms is 79%, with a minimum score of 37% and a maximum score of 97%. This implies that wheat farmers are not operating on the production frontier and can increase their TE score on average by as much as 21%. To achieve the TE score of the most efficient farmer, the output gain would be about 19% and 62% for the average farmer and the most inefficient farmer, respectively.

The average AE score is 80%, with a minimum score of 24% and a maximum score of 98%. This implies that on average allocative inefficiency (the lack of cost-minimizing behavior) accounts for a 20% loss in wheat income, or the potential to reduce cost (cost savings) by as much as 20%. To achieve the AE score of the most efficient farmer, the average farmer would realize a savings of about 18% of the total cost while the most inefficient farmer would reduce costs by as much as 76% of the total cost.

The average EE score is 64%, with a minimum score of 9%, and a maximum score of 93%. This implies that under the existing production technology, the average wheat farmer can realize greater wheat output by becoming more technically efficient and a 36% cost savings by optimizing the use of inputs given the prevailing prices. To achieve the EE level of the most economically efficient farmer, the average farmer could increase output and reduce costs by 31% while the

**Table 1.** Estimates for production function (OLS) and stochastic frontier (MLE).

Output (kgs)	OLS			MLE		
	Estimate	Std. Error	t value	Parameter	Std. Error	t-value
(Intercept)	1.926	5.737	0.336	2.676	3.982	0.672
Land (acres)	2.373***	0.620	3.827	1.964***	0.499	3.936
Seed (kgs/acre)	0.970	2.291	0.423	0.785	1.590	0.494
Fertilizer (kgs/acre)	0.328*	0.188	1.742	0.205	0.171	1.203
Herbicides (lts/acre)	2.895	2.083	1.390	0.837	1.412	0.593
Insecticides (lts/acre)	-3.444*	1.793	-1.921	-2.938*	1.535	-1.914
Pesticides (lts/acre)	2.714	1.977	1.373	1.517	1.367	1.110
Labor (man days)	-0.245	1.225	-0.200	0.547	0.997	0.549
Land * land	-0.283***	0.058	-4.875	-0.267***	0.055	-4.854
Land * Seed	-0.124	0.127	-0.975	-0.077	0.106	-0.729
Land * Fertilizer	0.008	0.014	0.545	0.011	0.013	0.851
Land * Herbicides	0.204	0.139	1.467	0.192	0.130	1.473
Land * Insecticides	-0.005	0.146	-0.034	0.139	0.134	1.037
Land * Pesticides	-0.201	0.139	-1.450	-0.035	0.125	-0.279
Land * Labor	0.009	0.095	0.090	0.033	0.085	0.392
Seed * Seed	-0.219	0.483	-0.453	-0.095	0.336	-0.282
Seed * Fertilizer	-0.029	0.038	-0.758	-0.009	0.034	-0.262
Seed * Herbicides	-0.504	0.423	-1.192	-0.154	0.290	-0.531
Seed * Insecticides	0.800**	0.370	2.164	0.652**	0.319	2.042
Seed * Pesticides	-0.123	0.417	-0.294	-0.094	0.306	-0.308
Seed * Labor	0.126	0.239	0.528	-0.118	0.204	-0.579
Fertilizer * Fertilizer	-0.050	0.034	-1.489	-0.041	0.032	-1.261
Fertilizer * Herbicides	-0.009	0.044	-0.218	-0.006	0.041	-0.150
Fertilizer * Insecticides	0.034	0.041	0.812	0.026	0.039	0.667
Fertilizer * Pesticides	0.004	0.044	0.080	0.053	0.044	1.215
Fertilizer * Labor	-0.009	0.029	-0.299	-0.016	0.026	-0.595
Herbicides * Herbicides	-0.710	0.538	-1.319	-0.833*	0.452	-1.843
Herbicides * Insecticides	0.292	0.363	0.804	0.277	0.310	0.893
Herbicides * Pesticides	-0.161	0.374	-0.430	0.450	0.351	1.282
Herbicide * Labor	-0.210	0.351	-0.598	-0.037	0.338	-0.110
Insecticides * Insecticides	-0.686	0.465	-1.477	-0.363	0.460	-0.790
Insecticides * pesticides	0.607*	0.338	1.795	0.575*	0.297	1.937
Insecticides * Labor	-0.005	0.271	-0.019	-0.065	0.253	-0.258
Pesticide * Pesticides	-1.424**	0.565	-2.519	-1.694***	0.479	-3.534
Pesticides * Labor	-0.602**	0.286	-2.103	-0.380	0.248	-1.531
Labor * Labor	0.009	0.159	0.055	0.037	0.144	0.254

Continued

$R^2$	0.950	-	-	-	-	-
Adjusted $R^2$	0.943	-	-	-	-	-
$F_{35,274}$	147.9***	-	-	-	-	-
$\sigma^2$	0.050	-	-	0.114	-	-
Lik.	42.770	-	-	57.698	-	-
$\lambda$	-	-	-	4.003***	0.881	4.542
$\sigma_v^2$	-	-	-	0.007	-	-
$\sigma_u^2$	-	-	-	0.108	-	-
$\gamma = \frac{\sigma_u^2}{\sigma_v^2}$	-	-	-	0.95	-	-

\*\*\*, \*\*, and \* represent the significance level at 1%, 5%, and 10%, respectively.

Table 2. OLS and MLE estimates of translog cost function.

Cost	OLS			MLE		
	Estimate	Std. Error	t value	Parameter	Std.err	t-value
(Intercept)	3.056	2.903	1.052	0.454	1.962	0.231
Ps/Pl	4.073***	1.136	3.585	2.857***	0.809	3.533
Pf/Pl	-2.499**	1.154	-2.166	-2.534***	0.902	-2.810
Ph/Pl	0.945	0.678	1.393	0.697	0.738	0.944
Pi/Pl	0.602	0.694	0.868	1.436**	0.654	2.197
Pp/Pl	-0.187	0.676	-0.276	-0.849	0.643	-1.322
Q	0.551*	0.319	1.727	0.622**	0.278	2.233
Ps/Pl * Ps/pl	0.532*	0.275	1.930	0.223	0.217	1.027
Ps/Pl * Pf/Pl	-0.042	0.212	-0.197	-0.086	0.211	-0.407
Ps/Pl * Ph/Pl	0.233*	0.138	1.684	0.252*	0.134	1.878
Ps/Pl * Pi/Pl	-0.066	0.143	-0.460	-0.126	0.117	-1.074
Ps/Pl * Pp/Pl	0.013	0.154	0.082	0.106	0.148	0.719
Ps/Pl * Q	-0.128**	0.058	-2.214	-0.194***	0.057	-3.375
Pf/Pl * Pf/Pl	-0.288	0.247	-1.166	-0.201	0.216	-0.929
Pf/Pl * Ph/Pl	0.014	0.163	0.088	-0.103	0.173	-0.596
Pf/Pl * Pi/Pl	0.214	0.156	1.371	0.422***	0.155	2.727
Pf/Pl * Pp/Pl	-0.081	0.189	-0.428	-0.286	0.201	-1.428
Pf/Pl * Q	0.156**	0.062	2.499	0.181***	0.054	3.389
Ph/Pl * Ph/Pl	-0.016	0.117	-0.136	0.107	0.112	0.955
Ph/Pl * Pi/Pl	-0.068	0.089	-0.767	-0.023	0.084	-0.272
Ph/Pl * Pp/Pl	0.041	0.082	0.496	0.019	0.082	0.226
Ph/Pl * Q	0.028	0.038	0.744	0.039	0.040	0.968
Pi/Pl * Pi/Pl	0.045	0.104	0.437	-0.017	0.099	-0.171
Pi/Pl * Pp/Pl	-0.008	0.077	-0.101	0.020	0.078	0.258

## Continued

Pi/Pl * Q	0.007	0.040	0.167	-0.013	0.042	-0.305
Pp/Pl * Pp/Pl	-0.056	0.109	-0.513	-0.075	0.112	-0.670
Pp/Pl * Q	-0.004	0.038	-0.112	0.017	0.043	0.394
Q * Q	0.052***	0.020	2.623	0.022	0.024	0.911
$R^2$	0.934	-	-	-	-	-
Adjusted $R^2$	0.928	-	-	-	-	-
$F_{27,282}$	147.7***	-	-	-	-	-
$\sigma^2$	0.046	-	-	0.103	-	-
Lik.	51.261	-	-	70.480	-	-
$\lambda$	-	-	-	3.681***	0.825	4.464
$\sigma_v^2$	-	-	-	0.007	-	-
$\sigma_u^2$	-	-	-	0.096	-	-
$\gamma$	-	-	-	0.93	-	-

\*\*\*, \*\*, and \* represent the significance level at 1%, 5%, and 10%, respectively.

**Table 3.** TE, AE, and EE for wheat production (pooled sample).

	Min	Max	Mean	Std.
TE	0.37	0.97	0.79	0.133
AE	0.24	0.98	0.80	0.125
EE	0.09	0.93	0.64	0.178

least efficient farmer could increase output and reduce cost by 90%.

### 5.3. Distribution of Efficiency Scores

**Figure 3** shows that the distribution of TE scores for the pooled survey sample is negatively skewed. The mean TE score for the pooled sample is ~80%, with 57% of the sampled farmers scoring above the average and 43% scoring below the average (**Table 3**). **Figure 4** shows that AE score is negative skewed. The mean AE score for the pooled sample is 80%, with 37% of the sampled farmers scoring below the average and 63% scoring above the average (**Table 3**). The minimum EE score is 64%, with 42% of the sampled wheat farmers operating below the average EE score. **Figure 5** depicts the histogram of EE scores shows a negative skewness, implying that the median is on the right of the mean score.

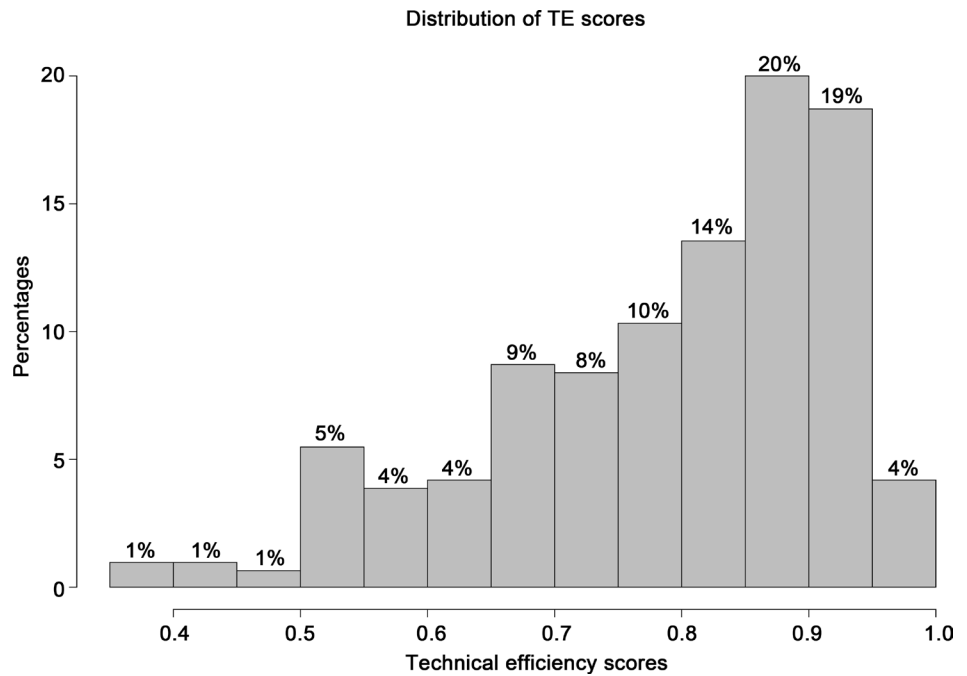
### 5.4. Factors Influencing Efficiency

In contrast to input and output factors used in estimating efficiency scores, household idiosyncratic factors were analyzed to explore sources of inefficiencies for the pooled sample data of the study area. Also, each ward's specific location was considered to capture heterogeneity in soil fertility, distance to urban areas, and infrastructure accessibility effect on TE, AE, and EE.

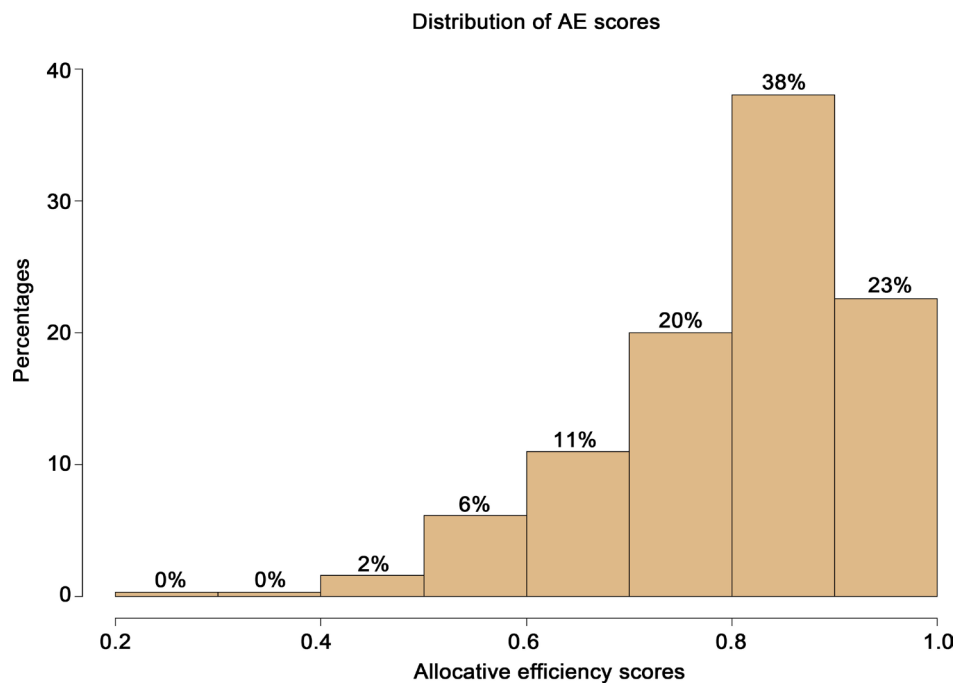
Of particular interest are the coefficients of the variables associated with con-

tract participation and farmers' association memberships since they are the indicators of farmers' participation in the value chain (coordination). **Table 4** shows that with the ignorability condition (without considering sample selection bias), participation in contracts and farmers' associations positively and significantly (5%, 1%, 1% level) influences TE, AE, and EE, respectively.

Conversely, age has a negative and significant (at the 5% level) effect on TE, AE, and EE. This suggests that older farmers are less efficient than younger far-

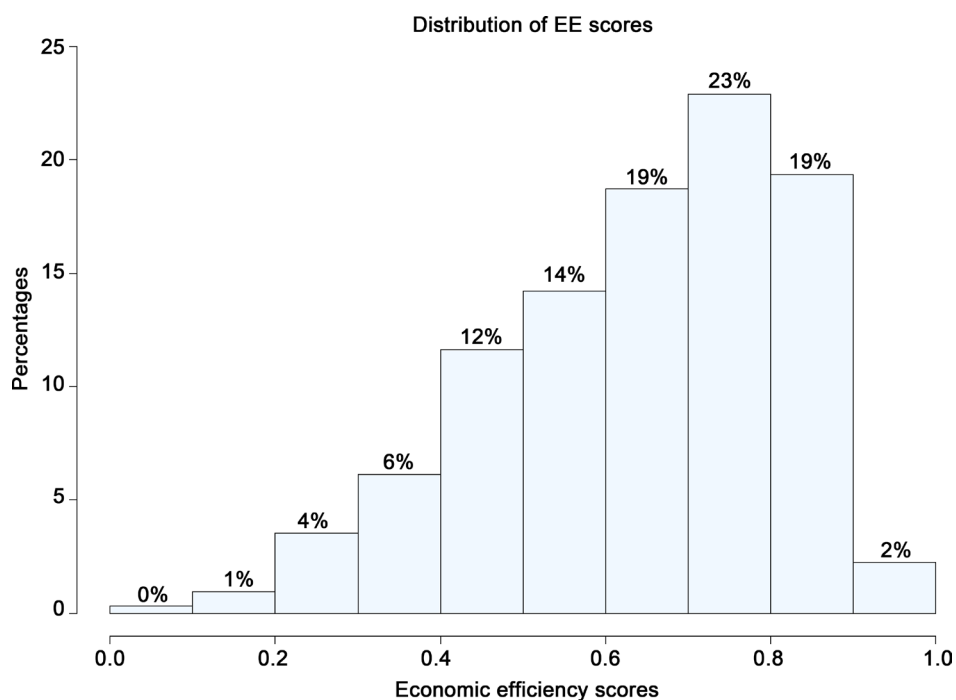


**Figure 3.** The distribution of TE scores of the pooled sample in the study area.



**Figure 4.** The distribution of AE scores of the pooled sample in the study area.





**Figure 5.** The distribution of EE scores of the pooled sample in the study area.

**Table 4.** Factors influencing efficiency (Tobit model).

Variables	TE		AE		EE	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	0.712***	0.053	0.730***	0.047	0.521***	0.068
Contract	0.057***	0.020	0.037**	0.018	0.069***	0.026
Membership	0.042***	0.015	0.074***	0.013	0.086***	0.019
Age	-0.002**	0.001	-0.001**	0.001	-0.002**	0.001
Education	0.004*	0.002	0.003	0.002	0.005*	0.003
Experience	0.001	0.001	0.001	0.001	0.002	0.001
Household composition	0.025	0.019	0.011	0.017	0.031	0.024
Age18 below	-0.026	0.019	-0.009	0.017	-0.031	0.025
Age18 to 50	-0.029	0.019	-0.016	0.018	-0.038	0.025
Age 50 up	-0.016	0.021	0.008	0.019	-0.012	0.028
Land leased	0.012	0.015	0.024*	0.014	0.029	0.020
Extension visit	0.007**	0.003	0.009***	0.003	0.012***	0.004
Meeting	0.000	0.007	-0.004	0.006	-0.003	0.009
Mbulumbulu	0.012	0.029	0.047*	0.026	0.043	0.038
Rhotia	0.025	0.031	0.040	0.028	0.049	0.040
Mondulijuu	0.011	0.029	0.006	0.026	0.017	0.038
Transport ownership	0.003	0.027	0.010	0.024	0.015	0.035
Farm equipment	0.044*	0.025	0.047**	0.022	0.077**	0.032
Livestock	0.046	0.028	-0.006	0.026	0.035	0.037
Hybrid seed	0.048**	0.023	0.037*	0.021	0.073**	0.030
Off-farm income	0.051***	0.020	0.051***	0.018	0.080***	0.026
Logsigma	-2.119***	0.040	-2.223***	0.040	-1.864***	0.040

mers. This result is plausible given that younger farmers are more receptive of new technologies and agricultural practices that increase production and minimize costs. This finding is consistent with those of other studies that found the managerial capability to allocate factors of production in cost-minimizing behavior decreases with age [28]. The coefficient of education is positively and statistically significant at the 10% level for TE and EE. This result indicates that the higher the level of education, the higher the TE and EE. Farmers with more education are more likely to adopt better farm management practices that improve their levels of efficiency. As to be expected, extension services (visits) influence TE, AE, and EE positively and significantly at the 5%, 1%, and 1% level, respectively. On-farm training conducted by extension officers enables farmers to acquire better and more cost-effective farm management practices. Off-farm income influences TE, AE, and EE positively and significantly at the 1% level. This could be because off-farm income facilitates purchases of factors of production at a certain point in time. A similar result is found in Chavas *et al.* [29]. Farm equipment is essential for wheat production in the study area, with ownership influencing TE, AE, and EE positively at the 10%, 5%, and 5% significance levels, respectively. Ownership of modern farm equipment ensures carrying out various operations in a timely manner and at a lower cost compared to hired services. Hybrid seeds which are known to yield higher production output in wheat crops have a positive and significant (5%, 10%, and 5% level) impact on TE, AE, and EE, respectively. The per unit cost of hybrid seed becomes lower than that of local seed because the production level of local seed is lower.

Land rent positively influences AE at the 10% significance level by maximizing profit while minimizing cost. Thus, farmers select best farm management practices that minimize their production costs to realize higher profits at prevailing market prices. In addition, the Mbulumbulu ward farmers seem to be better at minimizing costs than their counterparts in the other three surveyed wards that have better infrastructures and market accessibility. Mbulumbulu was the only surveyed ward where its farmers significantly operate with a least-cost combination at the 10% significance level.

## 5.5. Impact of Value Chain Participation on Efficiency

As mentioned earlier, we examined the impact of value chain participation on TE, AE, and EE. PSM was used to ascertain the sample selection bias of observables. Nearest neighbor and caliper radius matching algorithms were used to match the characteristics of both participants and nonparticipants. We found that the levels of efficiency rise when farmers participate in vertical and horizontal coordination.

### 5.5.1. Vertical Coordination Impact

The nearest neighbor (NN) of 1:1 implies that all the vertical coordination participants are matched by one nonparticipant from the control group that has the closest characteristics. The histogram in **Figure 6** shows the distribution of the

sample before and after matching. Because the distribution of participants (matched-treated) is dissimilar to the distribution of matched nonparticipants (matched-control), the TE effect of 6.2% under NN is still biased.

The matched participant and nonparticipant distributions under a caliper radius of 0.005 were similar (Figure 7). Out of 51 vertical coordination participants, 31 were dropped given a 0.005 caliper radius compared to only 2 being dropped

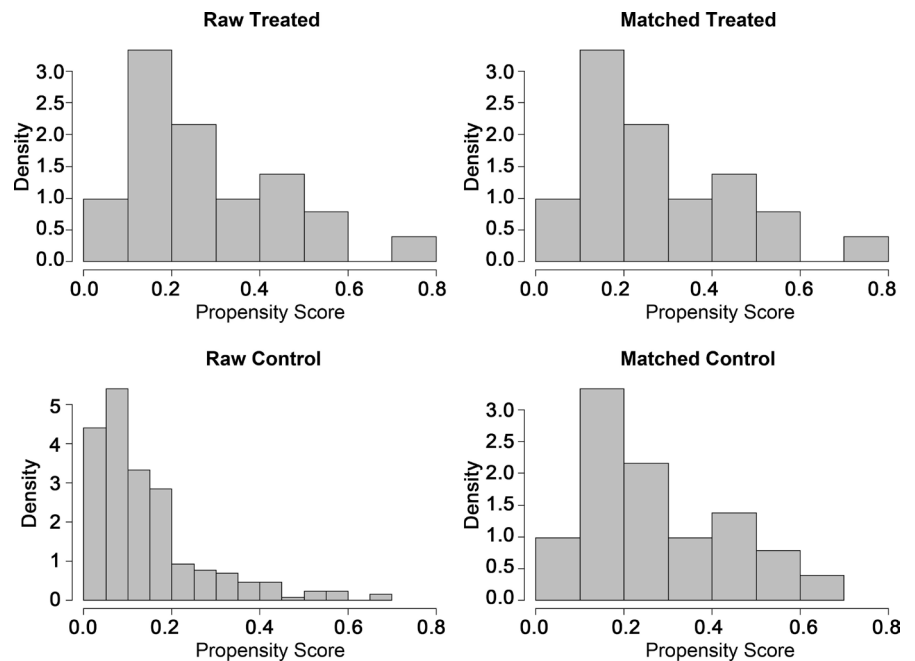


Figure 6. Vertical coordination histograms before and after matching by Nearest Neighbor algorithm of ratio 1:1.

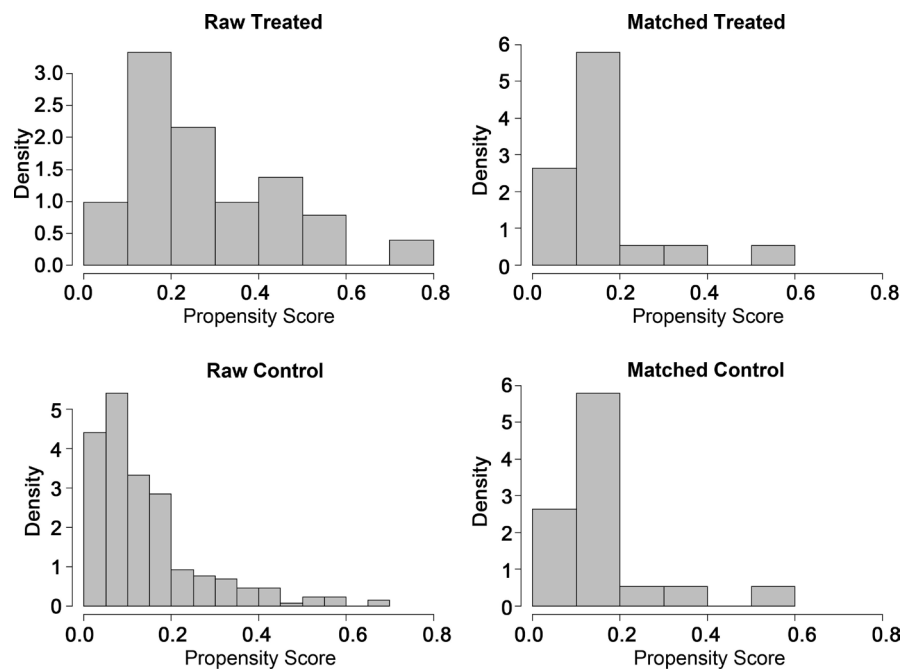


Figure 7. Vertical coordination histograms before and after matching by caliper radius of 0.005.

given a 0.13 caliper radius (Table 5). Increasing the caliper radius to 0.13, we obtained suitable similar matches (Figure 8) for the matched-treated and matched-controlled observations. An attempt to further increase the radius to accommodate at least 1 more participant did not prove worthwhile because the distributions between matched participants and nonparticipants became dissimilar.

The results show that participation in vertical coordination as measured by contracts with buyers increases TE by 6.8% more for participants than for nonparticipants. This finding is significant at the 5% level (Table 5). Likewise, vertical coordination participation under the caliper radius of 0.13 improves AE by 5.7% more than its counterpart at the 10% significance level (Table 6). As in both the TE and AE cases, vertical coordination participation under a caliper radius of 0.13 improves EE by 8.7% more for participants than for nonparticipants at the 5% significance level (Table 7).

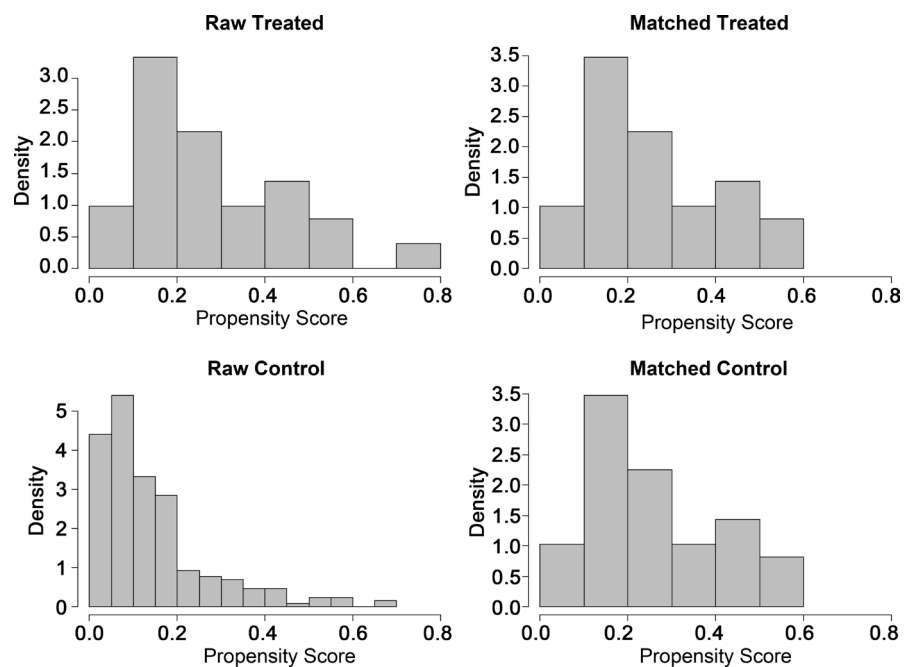


Figure 8. Vertical coordination histograms before and after matching by caliper radius of 0.13.

Table 5. TE effect due to participation in vertical coordination.

	TE effect	SE	t-value	p-value	Treated sample matched
Nearest Neighbor (1:1)	0.062	0.031	2.011	0.044	51
Caliper (0.005)	0.030	0.014	2.141	0.032	20
Caliper (0.01)	0.045	0.019	2.432	0.015	27
Caliper (0.02)	0.067	0.023	2.899	0.003	35
Caliper (0.03)	0.072	0.023	3.013	0.003	37
Caliper (0.10)	0.074	0.030	2.495	0.013	47
Caliper (0.13)	0.068	0.031	2.216	0.028	49

**Table 6.** AE effect due to participation in vertical coordination.

	AE effect	SE	<i>t</i> -value	<i>p</i> -value	Treated sample matched
Nearest Neighbor (1:1)	0.051	0.031	1.628	0.103	51
Caliper (0.005)	0.048	0.014	3.45	0.001	20
Caliper (0.01)	0.054	0.017	3.263	0.001	27
Caliper (0.02)	0.059	0.022	2.619	0.009	35
Caliper (0.03)	0.060	0.023	2.635	0.008	37
Caliper (0.10)	0.062	0.030	2.050	0.040	47
Caliper (0.13)	0.057	0.031	1.848	0.065	49

**Table 7.** EE effect due to participation in vertical coordination.

	TE effect	SE	<i>t</i> -value	<i>p</i> -value	Treated sample matched
Nearest Neighbor (1:1)	0.077	0.043	1.779	0.075	51
Caliper (0.005)	0.061	0.021	2.940	0.003	20
Caliper (0.01)	0.075	0.026	2.901	0.004	27
Caliper (0.02)	0.091	0.032	2.892	0.004	35
Caliper (0.03)	0.097	0.032	2.984	0.003	37
Caliper (0.10)	0.095	0.0414	2.298	0.022	47
Caliper (0.13)	0.087	0.043	2.031	0.042	49

**Table 8.** TE effect due to participation in horizontal coordination.

	TE effect	SE	<i>t</i> -value	<i>p</i> -value	Treated sample matched
Nearest (1:1)	0.077	0.021	3.785	0.000	122
Caliper (0.03)	0.061	0.017	3.544	0.000	109
Caliper (0.04)	0.064	0.018	3.585	0.000	113
Caliper (0.05)	0.063	0.018	3.534	0.000	114

### 5.5.2. Horizontal Coordination Impact

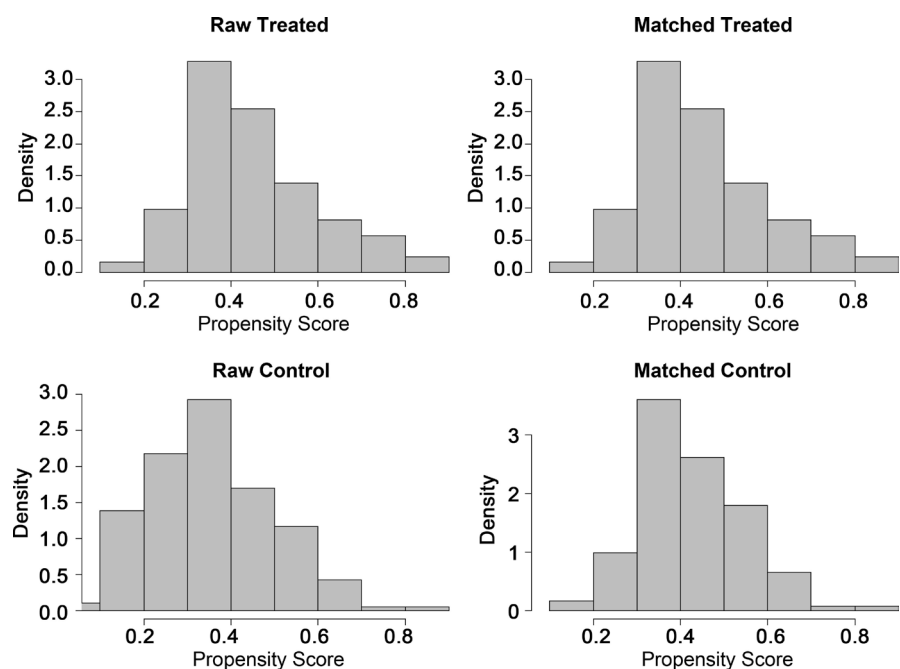
As in the case of vertical coordination, an attempt was made to use the nearest neighbor (NN) technique for horizontal coordination matching. The results are shown in **Table 8** for farmers who participated in horizontal coordination as measured by farmers' association memberships. The results indicate an improvement in TE of 7.7% for participants compared to non-participants. However, the results are biased because the histogram distributions for matched-treated and matched-control groups are dissimilar (**Figure 9**). Thus, the need for a better matching procedure for the sample is important.

Accordingly, we employed caliper radius matching for 122 observations. The first caliper radius considered was 0.03, which had 109 good matches, with 13 observations being dropped. When we increased the radius to 0.05, 114 treated observations were found to be good matches, with only 8 observations being dropped (**Table 8**). Further increases of the radius did not give good matches;

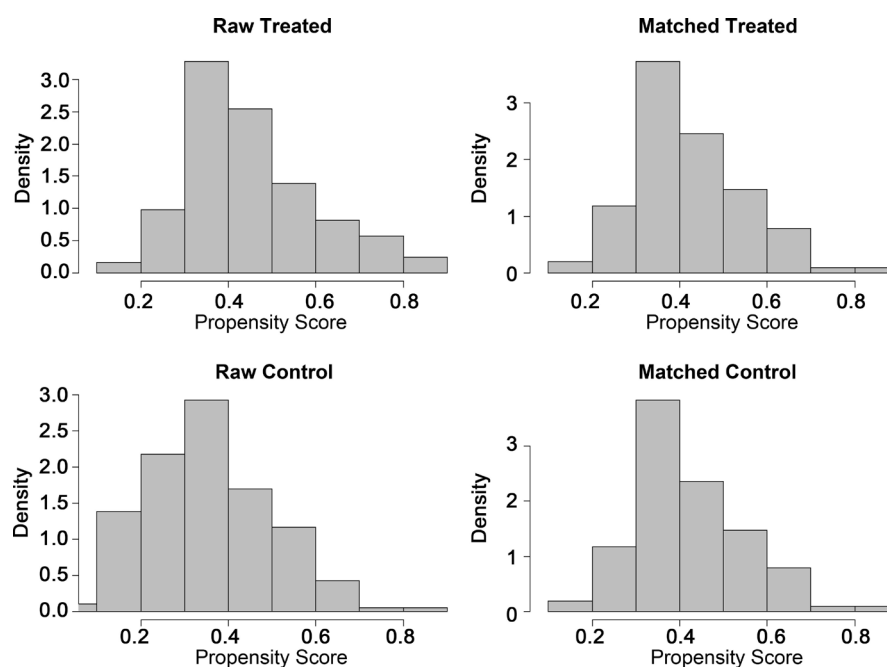
the matched distributions for treated and control groups were dissimilar like in the nearest neighbor (NN) matching procedure in **Figure 9**. Therefore, with a caliper radius of 0.05, horizontal coordination participants were found to improve their TE by 6.3% more than nonparticipants at the 1% significance level. Using a caliper radius of 0.05 for matched participants and nonparticipants, horizontal coordination as measured by farmers' association memberships improved AE by 9.5% more for participants than for nonparticipants at the 1% significance level (**Figure 10**). There was no significant difference in the AE effect across the matching methods, implying good observations for the matches (**Table 9**). Likewise, with a caliper radius of 0.05, participants improved their EE by 11.6% more than did nonparticipants at the 1% significance level (**Table 10**).

## 6. Conclusions and Recommendations

The general objective of this study was to explain why wheat production is not responding to the increasing demand for wheat products in Tanzania. One factor considered to explain the situation was the efficiency levels of wheat production units. TE, AE, and EE were first estimated over the pooled sample without the consideration of selection bias for participants and nonparticipants of the value chain. We employed the translog functional form for production and cost functions in a stochastic frontier analysis. Land, fertilizer, and insecticides were found to significantly influence the level of wheat output. The translog cost function revealed that seed, fertilizer, and insecticide prices monotonically increased with production cost, except for fertilizer price which violated the monotonicity assumption at the 5% significance level. Total production cost was found to significantly increase with the quantity of wheat output, which means



**Figure 9.** Horizontal coordination histograms before and after matching by Nearest Neighbor algorithm of 1:1 ratio.



**Figure 10.** Horizontal coordination histograms before and after matching by caliper radius of 0.05.

**Table 9.** AE effect due to participation in horizontal coordination.

	AE effect	SE	<i>t</i> -value	<i>p</i> -value	Treated sample matched
Nearest (1:1)	0.101	0.018	5.688	0.000	122
Caliper (0.03)	0.096	0.016	5.927	0.000	109
Caliper (0.04)	0.096	0.0167	5.769	0.000	113
Caliper (0.05)	0.095	0.017	5.722	0.000	114

**Table 10.** EE effect due to participation in horizontal coordination.

	EE effect	SE	<i>t</i> -value	<i>p</i> -value	Treated sample matched
Nearest (1:1)	0.132	0.026	5.080	0.000	122
Caliper (0.03)	0.115	0.023	5.076	0.000	109
Caliper (0.04)	0.117	0.023	5.019	0.000	113
Caliper (0.05)	0.116	0.023	4.959	0.000	114

that the monotonicity assumption of translogcost function holds for existing production technology.

The mean TE, AE and EE scores are all less than 100% implying that using the same factors of production at existing market prices, wheat farmers can significantly increase their output if appropriate policies or programs are implemented to improve the efficiency of wheat production. EE could be increased by 36% when TE and AE are attained. The factors that influenced TE, AE, and EE the most were contracts, farmers' association memberships, education, extension visits, farm equipment, hybrid seed, and off-farm income.

Measuring the net effect of value chain participation on TE, AE, and EE using

the PSM technique reduces biases associated with observed variables. Using caliper radius matching, the vertical and horizontal coordination participants improve their TE, AE, and EE scores more than do nonparticipants. Further comparisons show that vertical coordination participation improves TE more than horizontal coordination participation. Also horizontal coordination participation improves AE more than vertical coordination participation. The implication is that vertical coordination is about honoring the contractual agreement put forth by buyers on various aspects including the technical requirements and quantity to be delivered. Accordingly, the farmers tend to utilize their factors of production more efficiently when meeting their contractual obligations, resulting in a greater level of technical efficiency compared to allocative efficiency. On the other hand, horizontal coordination is about working in groups where most transactions are done in bulk thus reducing the cost of production per unit. Buying inputs and selling output jointly is advantageous to farmers because it is a cost-minimizing strategy. Thus, farmers who join associations produce more at the least-cost combination which has a more direct implication on allocative efficiency than on technical efficiency.

Overall, our results recommend that in order to improve farm-unit efficiency, farmers need to participate in the value chain (vertical and horizontal coordination) as it has been proven that participation improves farm-level efficiency. In addition, modern farm technology, higher education, and extension services empower farmers to increase their farm-level output and efficiency. Lastly, more off-farm employment activities are needed to supplement on-farm income to purchase more factors of production.

The scope of this paper was on application of SFA and PSM approaches to analyze efficiency using firsthand data collected from Northern part of Tanzania. The future direction should focus on using panel data if available with large sample size across the country where more representatives will be included in the analysis. This is because the regional heterogeneity of weather condition for wheat production across the country could bring varied efficiency levels that might call for a different policy measures. Also it would be fruitful to analyze in details factors that motivates and barriers that prevent wheat producers from value chain participation.

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