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The Relationship Between Off-Farm Work and Farm Management: A Case of the Tanzania Living Standards Measurement Survey

Hussein N. Nassoro
Institute of Finance Management (IFM)
hussein.nasoro@ifm.ac.tz

Abstract

Rural households in Tanzania are increasingly diversifying their livelihoods by shifting labor from farming to off-farm activities. However, little is known about how this shift impacts farm management. This research addresses the gap by utilizing panel data derived from the Living Standards Measurement Survey (LSMS). The study assesses the effect of off-farm work on farm technical efficiency by estimating the farm production function using a Stochastic Frontier Analysis (SFA) approach. The findings reveal that the squared term of farm-specific off-farm hours had a positive and highly significant coefficient, indicating that increased participation in off-farm work negatively impacts farm technical efficiency. These results suggest that policies aimed at improving farm productivity should account for the fact that greater involvement in off-farm work diminishes farmers' ability to effectively manage their farms.

Keywords: *Cobb Douglass, Off-farm work, Technical efficiency, Stochastic Frontier Analysis*

1. Introduction

Most developing countries, including Tanzania, rely on agriculture as a key source of livelihood (Anang, 2020; Ma et al., 2022, Ellis & Mdoe, 2003). The agricultural sector employs nearly two-thirds of the population and is dominated by smallholder farmers with an average farm size of 0.5 hectares (reference). Consequently, the growth and development of this sector is a critical pathway out of poverty and food insecurity (Diao et al., 2010; Kassie et al., 2013; Collier & Dercon, 2014; Dawson et al., 2016). However, the sector's contribution to the overall Gross Domestic Product (GDP) has been declining over the years due to the emergence of other economic sectors such as mining services, and manufacturing.

Despite its importance, the performance of the agricultural sector has been underwhelming. According to the Bank of Tanzania (BOT) report, the sector has experienced growth rates of less than 5% for more than two decades. Several challenges hinder its progress, including poverty, low levels of investment, credit constraints, and limited market access. As a result, the adoption of improved technologies has been constrained, forcing smallholder farmers to rely on rudimentary methods of production. In response to liquidity constraints and declining farm incomes, many smallholder farmers have diversified their production and now rely on multiple sources of income apart from farming (Anang, 2020). Many farm households often resort to alternative means like off-farm activities to deal with the challenges of income variability (Gideon Danso-Abbeam, 2017).

This trend has been widely documented in research reports (Ma et al., 2022, Cheng & Wen, 2011; Mduma, 2006; Dimeva & Seni, 2010; Ellis & Mdoe, 2003). Off-farm work refers to any economic activity undertaken by household members outside farming as an additional source of income. Participation in off-farm activities has become a common global phenomenon (Cheng & Wen, 2011), with research suggesting that significant amounts of income are generated through these activities. Off-farm work is estimated to contribute more than 50% of rural household income (Ellis & Mdoe, 2003; Demova & Seni, 2010, Ma et al., 2022). Unlike farm income, this income is characterized by lower risks of covariance, which has led some development experts to view off-farm work as a potential vehicle for reducing poverty.

Household participation in off-farm work is associated with a reallocation of labor previously dedicated solely to farming activities. This practice often reduces the time allocated to farming, and the possibility of compensating for the reduced labor through hiring is limited. Singh et al. (1986) argue that rural labor markets are often imperfect, making it difficult to hire additional labor. This raises significant concerns about how off-farm work participation affects farm management and technical efficiency. Similar observations were made by Rutasitara (2004) and Lien et al. (2010), who noted that in countries where rural off-farm activities predominantly rely on unpaid family labor and apprenticeships, the impact on farm management (particularly technical efficiency) warrants closer examination.

Empirical studies addressing this issue in Tanzania remain limited. Understanding how farm technical efficiency and management are influenced by labor reallocation due to off-farm work is critical in a country where rural development policies heavily emphasize on farm development. In other regions, empirical evidence on the impact of off-farm work on farm efficiency indicates mixed results. For example, studies by Anang (2021), Mochelebelele and Winter-Nelson (2000), Tijani (2006), Haji (2007), Preiffer et al. (2009), Babatunde (2013), Kilic et al. (2009), and Goodwin and Mishra (2004) provide varying findings. Goodwin and Mishra (2004), Cheng and Wen (2011), and Kilic et al. (2009) observed adverse effects of off-farm activities on farming. Conversely, Ahmed and Melese (2018) reported that farmers engaged in off-farm work achieved significantly higher technical efficiency compared to non-participants. These contrasting findings highlight the need for detailed, context-specific research in individual countries, as the impact of off-farm work on farm efficiency varies significantly across contexts.

Thus, the objective of this study is to assess how off-farm work participation affects farm technical efficiency. The study is guided by the null hypothesis that increased participation in off-farm work reduces the level of technical efficiency. This article is organized as follows: it first presents a theoretical model analyzing rural household behavior in the presence of off-farm activities. The impact of off-farm work participation is examined within the context of farm performance, focusing on technical efficiency, using a stochastic frontier approach. A review of empirical literature on the effect of off-farm work on farm performance is then presented to lay the foundation for the analysis. Finally, the conclusion and recommendations are provided.

2. Conceptual Framework

The effect of off-farm work on farm performance can be analyzed using a basic agricultural household model. This model assumes that markets are perfect, meaning that if engaging in off-farm activities reduces the labor available for farm production, the resulting labor shortfall can be compensated for by hiring labor from the market. This is feasible because the household is assumed to generate a relatively higher income from off-farm activities. Under these conditions, the standard condition for profit maximization by a rural household remains unchanged. However, there is no evidence in the literature confirming the presence of perfect markets in developing countries. Charvas et al. (2005) argue that small-scale agriculture in less developed regions faces several constraints, including labor market rigidities and technological interdependencies between farm and off-farm activities. Market imperfections have a broad definition but can generally be described as the inability to sell household labor in the market, liquidity constraints that hinder the purchase of agricultural inputs, and the inability to sell crop produce due to various factors, such as high transaction costs. Because of these characteristics, the theoretical profit-maximizing behavior of the household is no longer separable (Pfeiffer et al., 2009).

In this context, the theoretical framework considers a household as the one endowed with a fixed amount of time that can be allocated to farm production, off-farm activities, or leisure, as outlined in the agricultural household model. The household generates income either by selling farm products in the market, where the price is denoted as PP, or by earning wages from off-farm activities (WW). For this study, the approach to modelling production functions follows the framework of Kumbhakar (2002), with some modifications, as outlined in Equation 1.

$$F(L) = f(L) - h(L)u \tag{1}$$

where $f(.)$ specify the effects of inputs

$h(.)$ = Production efficiency

u = a random noise or deviation on a stochastic production frontier.

The objective function of the household is to derive utility from the consumption of purchased commodities or farm-produced goods and leisure. However, the expected utility is constrained by the availability of time and income. Thus, household behavior is expressed in Equations 2, 3 and 4.

$$MaxE(C, L_s) \tag{2}$$

Subject to

$$C = P*[f(L) - h(L)u + W*L_m \tag{3}$$

$$E = L + L_s + L_m \tag{4}$$

Equation 2 expresses the expected utility of the households, while Equation 3 reflects the consumption equation. Combining both Equations yields Equation 5.

$$EU((P*(f(L) - h(L)u + w*L_m)(E - L_s - L_m) = 0 \tag{5}$$

The derivation of the first order necessary Kuhn Tucker conditions provides the optimal allocations of time for farm production as well as for off-farm employment. Thus, first-order conditions are derived in Equations 6 and 7.

$$\partial EU(.) = \frac{\partial EU(.)}{\partial C} * P(f_L - h_L\mu) - \frac{\partial EU(.)}{\partial L} = 0 \tag{6}$$

$$\frac{\partial EU(.)}{\partial L_m} = \frac{\partial EU(.)}{\partial C} * w - \frac{\partial EU}{\partial L} \leq 0L_m \tag{7}$$

$$\frac{\delta EU}{L_m} - Lm = 0 \tag{8}$$

Equation 8 reflects optimal allocation of time for off-farm activities. From this perspective, two optimal conditions may exist. First, inequality constraints hold if a household decides not to participate in off-farm work. Alternatively, equality constraints hold if the household decides to engage in off-farm activities. Two assumptions can be applied to solve the equations described above. The first assumption is that a household may choose to work in both activities—farm and off-farm employment—resulting in an interior solution. The second assumption is that the household may opt to work exclusively on the farm, leading to a corner solution.

In the case of an interior solution, the household undertakes both activities, making them interdependent. By combining Equations 5 and 6, the optimal allocation of labor for off-farm and on-farm production is obtained. The optimal labor allocation is then substituted into the production functions for off-farm and on-farm activities. This interdependence between the two equations introduces the issue of endogeneity. The details of how this issue is resolved are provided in the relevant subsection of the estimation procedure.

3. Literature Review

As discussed earlier, the effect of off-farm work on farm performance has received limited research attention. The few studies conducted so far present mixed findings, with the effect of off-farm work reported as positive, negative, or neutral, depending on how households are integrated into factor or product markets (Alvarez et al., 2005). For example, Pfeiffer et al. (2009) analyzed the effect of off-farm income on agriculture using household survey data from rural Mexico and observed that off-farm income had a significant negative effect on agricultural production. They examined the components of this negative effect to understand the mechanisms by which off-farm activities may influence farming. Their findings revealed that a marginal increase in wage rates prompted households to allocate more time to off-farm work at the expense of family labor for crop production, leading to a decline in farm labor supply. However, the study also noted positive impacts, such as increased use of purchased inputs due to reduced liquidity constraints and slight gains in efficiency linked to total factor productivity. The study concluded that households tend to substitute family labor with other inputs when off-farm returns increase.

Anang (2021) assessed the determinants of participation in off-farm activities and examined their impact on the technical efficiency of maize production in eastern Ethiopia using household data. By estimating a stochastic frontier production function, the study found that off-farm activities positively influenced both maize production and productivity. Participants in off-farm work were found to be more technically efficient than non-participants. This complementary relationship between off-farm and farming activities was attributed to the reinvestment of off-farm income into farming through the purchase of labor and technologies such as tractors.

Lien et al. (2010) used farm-level panel data to estimate the determinants and impact of off-farm work participation on farm performance. They modeled households to participate in both activities—farm production and off-farm work—using a simultaneous system of off-farm and farm production functions. Their results indicated that factors such as age, marital status, number of children, farming region, and farm output influenced farm work decisions. In contrast to Pfeiffer et al. (2009), Lien et al. (2010) found no evidence of a negative impact of off-farm work on farm production or technical efficiency. Instead, they noted that farmers and their partners who engaged in off-farm work were able to increase production to some extent.

Given that smallholder farmers in developing countries face credit constraints, participation in off-farm work is often seen as a strategy to overcome these challenges, leading to the adoption of improved farming technologies. For instance, Fernandez-Cornejo and Hendricks (2003) developed an econometric model to examine the interaction between off-farm work and the adoption of herbicide-tolerant crops and their impact on household income. They found no definitive tradeoff between hours spent on farming and off-farm work, but they reported a statistically significant relationship between off-farm work and technology adoption. Their study also highlighted structural relationships, including the fact that owners of small farms were more likely to work off-farm and adopt labor- or management-saving technologies.

Using household survey data, Babatunde (2010) analyzed the effect of off-farm income on farm output, expenditure on purchased inputs, and technical efficiency. The findings revealed that off-farm income had a positive and significant effect on farm output and demand for purchased inputs. However, there was no strong evidence that off-farm income significantly improved technical efficiency, apart from marginal efficiency gains in a few households. Contrary to the view that off-farm activities create competition for labor and negatively affect farm production, Babatunde (2010) observed complementary and positive spillover effects between the farm and off-farm sectors. The study recommended strengthening rural infrastructure and developing efficient financial markets to foster both economies and address credit constraints.

Fernandez-Cornejo (2007) analyzed the effects of off-farm work at two levels. At the farm level, he observed that off-farm work reduced technical efficiency, while at the household level, off-farm work increased technical efficiency. Additionally, the study found that higher off-farm income was associated with the adoption of agricultural innovations that saved managerial time, whereas lower off-farm income was linked to the adoption of managerially intensive technologies. Similarly, Anriquez and Daidone (2008), in the FAO study, examined the linkages between the farm and off-farm sectors in rural Ghana using a stochastic frontier approach. In their study, they analyzed input demands and agricultural transformation driven by the expansion of the rural off-farm sector under different market conditions, including perfect and missing markets for inputs and outputs. The study found that Ghanaian farms exhibited high levels of technical efficiency and that the expansion of the off-farm sector increased the demand for agricultural inputs, including land. Smaller farms were generally found to be more efficient. However, evidence of a significant contribution of the off-farm sector to production efficiency was not robust. The study also noted that off-farm work exhibited increasing returns to scale in household production.

Reardon et al. (1994) described the linkage between off-farm work and farm investment in African households. However, their study lacked empirical testing of hypotheses using statistical measures. They observed that off-farm work could have a polarized effect on farm management. In some cases, off-farm work drew resources away from farming, while in other cases, it served as collateral, allowing households to access credit. Reardon et al. (1994) supported the idea that credit initiatives targeting off-farm activities might be more effective than those aimed at farm production due to lower associated risks. If positive linkages between farm and off-farm economies are established, policymakers may prioritize fostering off-farm activities rather than providing concessional credit for farm production.

All the studies cited above applied an agricultural household model to derive household behavior in terms of labor allocation between farm and off-farm activities. However, Pfeiffer et al. (2009) provided a detailed analysis of the agricultural household model and its application thus offering a clear understanding of the topic. Their model was later adopted by Lien et al.

(2010) in their analysis of off-farm work in Norway and it is consistent with the household model described by Singh et al. (1986).

4. Econometric Model

To estimate the effect of off-farm work participation on farm technical efficiency, this study employed a standard production function. A stochastic frontier model was applied, consistent with approaches used in studies by Green (2004), Lien et al. (2010), and Pfeiffer et al. (2009). Panel data was constructed by appending waves 1 and 2 thus enabling the estimation of a stochastic frontier model with a time dimension.

$$Y_{it} = f(x_{it}, z_i) + v_{it} \pm \mu_{it} \tag{9}$$

Where i=1..............N

t=1..............T, in which, in our case, T=2 for panel data and 0 for each NPS wave.

$$= = \alpha + \beta x_{it} + \tau z_i + v_{it} \pm \mu_{it},\ \mu_{it} \geq 0$$

$$Z_{it} = f(y_{it}, x_i) + v_{it} \pm \mu_{it} \tag{10}$$

Y_{it} is the farm output of maize for I households in a period t. x_{it} is the vector of inputs such as fertilizer, labor, land, pesticides, and seeds. Z_{it} represents hours of off-farm work by I households in a period t.

$$v_{it} \approx N[0, \sigma_u{}^2],$$

$$u_{it} = [U_{it} \mid \text{Where } u_{it} \approx N[0, \sigma_U{}^2] \perp v_{it}$$

The effect of household off-farm labor supply on farm performance was conceptualized as a simultaneous equation system. The first equation described the effect of off-farm labor supply on farm production, while the second equation depicted the off-farm labor supply equation and its determinants. The two equations are interdependent, as farm production depends on the number of labor hours allocated to off-farm work, and off-farm labor supply is influenced by farm production.

In the first equation, the farm production level was expressed as a function of several input factors, including the log of labor inputs (measured in man-hours), the log of total fertilizer (measured in kilograms), the log of cultivated area (measured in acres), the log of off-farm labor supply (measured in off-farm hours allocated), and the log of machinery and seeds. Additionally, other factors hypothesized to influence farm production levels were included in the equation.

Lien et al. (2010) identified several variables that determine both the production function and the off-farm work equation. These variables were considered empirically relevant to Tanzania and were therefore included in the analysis. This study incorporated the age of the household head, educational level, and household size, as these variables are known to influence participation in off-farm work and potentially affect the level of technical efficiency on the farm.

4.1. Form of a Production Function

Stochastic Frontier Analysis (SFA) requires the estimation of a production function to identify the contributing input factors in the final output. However, various forms of production functions can be estimated, and the choice of the functional form may influence the outcome of the analysis. Therefore, it is important to discuss the selection of the production function within the context of this study. A production function can take several forms, including linear, Cobb-Douglas, Translog, polynomial, and Constant Elasticity of Substitution (CES).

According to Greene (2005), the Cobb-Douglas and Translog models overwhelmingly dominate the literature on stochastic frontier and economic inefficiency estimation. Several studies, including those by Lien et al. (2010), Karamagi (2004), Kibaara (2005), and Pfeiffer et al. (2009), have applied the Cobb-Douglas and/or Translog models. The question of which model is superior remains an area of research. For instance, Karamagi (2004), Kibaara (2005), and Lien et al. (2010) applied both methods and conducted tests using the generalized likelihood ratio test to determine the most appropriate functional form. The generalized likelihood ratio test is given by Equation 11.

$$\lambda_{LR} = 2[L(H_1) - L(H_0)] \tag{11}$$

Where $L(H_1)$ and $L(H_0)$ are the maximum values of the log-likelihood function under the alternative and null hypothesis. A condition arises for rejecting or accepting the null hypothesis if $\lambda_{LR} \succ \chi^2 C$. Some authors reject the Translog production function in favor of the Cobb-Douglas function, while others advocate the opposite. For instance, Dutra et al. (2007) argue that the Translog production function is more flexible and can approximate any production function. A test conducted by the authors rejected the specification of the Cobb-Douglas function in favor of the Translog model.

Kibaara (2005), in analyzing the technical efficiency of maize production in Kenya, determined the appropriate functional form between the restrictive Cobb-Douglas and the Translog production functions by testing the null hypothesis through the estimation of four functional models: Cobb-Douglas, Translog, Quadratic, and Transcendental. The analytical results produced similar measures of technical efficiency across the models. However, Kibaara chose to focus on the Translog production function due to its greater flexibility compared to the Cobb-Douglas function. The Quadratic function was excluded because it did not capture the interaction terms of inputs rather it generated contradictory signs in the inefficiency model. Similarly, the results from the Transcendental production function were the lowest and were therefore not considered. Similarly, Lien et al. (2010) applied both Cobb-Douglas and Translog production functions and concluded that the Translog function is more robust than the Cobb-Douglas function.

5. Data Sets and Estimation

This study utilized LSMS datasets of Tanzania to examine how farmers manage farm production alongside participation in off-farm work. As the study focused on the relationship between farming and off-farm activities, it exclusively targeted rural areas. The data showed that households cultivated a variety of crops, including paddy, maize, beans, cowpeas, groundnuts, and others.

5.1. Variables Used

The variables used to analyze the effect of off-farm labor participation on farm production included:

i) *Log of output*: The logarithm of total output harvested from all plots owned by a household, measured in kilograms.
ii) *Log of area*: The total area of all plots used for production within a household, measured in acres.
iii) *Log-fert*: The logarithm of fertilizer applied. Organic and inorganic fertilizers were assumed to have equivalent nutrient composition and were measured in kilograms.
iv) *Value of seeds, pesticides, and machinery:* Incorporated as inputs.
v) *Log of labor:* The number of man-days allocated to farm production.
vi) *Age of household head:* Measured in years. Age was used as a proxy for farming experience, with fewer years reflecting lower levels of experience, which may affect technical efficiency.
vii) *Household size:* Measured as the number of people in a household. This variable captured the availability of labor resources and its potential correlation with technical efficiency.
viii) *Log of off-farm hours:* Used to measure participation in off-farm activities, calculated as the number of hours allocated to off-farm work.

Participation in off-farm work was assessed using the approach of Lien et al. (2010). Specifically, the log of off-farm hours was used to estimate its effect on farm production, while farm-specific off-farm hours were incorporated into the inefficiency equation. Farm-specific off-farm hours were calculated by taking the average off-farm hours at each sampling unit. Missing data in different variables were resolved through imputation. Importantly, the study did not distinguish between participants and non-participants in off-farm work.

5.2. System of Simultaneous Equations and Endogeneity

The relationship between off-farm and farm work was modeled using two structural simultaneous equations. This system, as discussed earlier, presented a problem of endogeneity. To address this issue, the Two-Stage Least Squares (2SLS) method was applied, following a similar approach to Lien et al. (2010). According to Verbeek (2008), 2SLS is an effective technique for resolving endogeneity issues derived from simultaneous equation systems. The reduced-form equations were derived, and structural equations were estimated by replacing endogenous variables on the right-hand side with predicted values from the reduced forms.

To ensure that the technical efficiency equation satisfied the assumption of identically independently distributed (iid) errors, the method proposed by Battese and Coelli (1995) was used. In this method, both the production frontier and its technical efficiency equation are estimated simultaneously. Two waves of panel data were appended to estimate the effect of off-farm work participation on farm technical efficiency, and a Stochastic Frontier Analysis (SFA) was applied. Relevant diagnostic tests were conducted at each analytical step before proceeding to subsequent stages.

5.3. Model Selection and Panel Effects

The analysis began with the estimation of a Cobb-Douglas production function, which is the simplest functional form. Given the use of panel data, it was necessary to determine whether a panel data approach or an Ordinary Least Squares (OLS) model should be applied. A Breusch and Pagan Lagrangian multiplier test was conducted (Cameron and Trivedi, 2010) to check for the presence of panel effects based on OLS residuals. The results of the Breusch and Pagan test indicated a significant difference at the 5% level ($P < 0.05$), leading to the rejection of the null hypothesis of no panel effects. This provided justification for using a panel data approach in subsequent analyses.

A further test was conducted to determine whether the Cobb-Douglas function or Translog production function was more appropriate for the NPS data. This involved a test of functional form. Both Translog and Cobb-Douglas models were estimated and subjected to a Hausman test, which showed a significant difference at the 1% level. Similar approaches were used by Lien et al. (2010) in Norway and by IFPRI (2013) in Uganda, which used a panel dataset of National Household Surveys to evaluate the impact of off-farm earnings on farm production. The results of this study supported the null hypothesis that the Cobb-Douglas function was a better fit than the Translog model thus justifying its use for the dataset.

5.4. Testing for Relevant Variables in the Cobb-Douglas Model

To proceed with the Cobb-Douglas production function analysis, a test was conducted to compare a restricted model with a parsimonious model. The aim was to determine whether the predicted log of off-farm hours was a relevant variable in the production function. A likelihood ratio test was performed, which showed a significant difference at the 1% level ($P < 0.01$), confirming the importance of including the predicted log of off-farm hours in the estimation of the production function. This provided further justification for using the Cobb-Douglas production function in subsequent analysis.

6. Findings and Discussion

6.1. Descriptive Statistics

Based on the analysis, the mean household size is different across the waves. The standard deviation for household size in the second wave was also much higher than in the first wave, indicating greater variation in household sizes among households in the second survey. While the minimum household size remained the same across both data sets, the maximum household size was recorded at 35 people. Household size serves as an indicator of the labor resources available within a household, which can be utilized for various economic activities, including off-farm work. Households with fewer family members may be compelled to hire labor from the market to complete tasks that would otherwise be performed by family members in larger households. Conversely, households with relatively few members have a lower level of consumption compared to larger households.

The log of labor per household followed the trend of household size, appearing higher in the second wave than in the first wave. However, the mean for areas under cultivation remained nearly unchanged between the two waves, with a standard deviation that also showed little variation. This suggests that the total area used for maize production did not change significantly between the first and second waves. While the cultivated area may have remained stable, it is possible that farming systems were evolved due to the adoption of inputs. However, this specific aspect was not tested in the analysis.

Table 1: Descriptive Statistics

	NPS 1				NPS 2			
Variable	Mean	Std.Dev	Min	Max	Mean	Std.Dev	Min	Max
Hhsize	5.149	2.830	1.000	26.000	5.590	3.240	1.000	35.000
Log_lab	1.741	0.392	2.301	5.079	3.993	0.920	0.000	6.628
Logseed	3.654	0.336	2.301	5.079	8.616	0.794	4.605	11.513
Logharv	2.446	0.503	0.477	4.176	5.460	1.253	0.253	8.343
Logfert	2.247	0.486	0.000	4.699	5.180	1.230	1.099	8.854
log_off_h	1.345	0.441	0.000	1.996	0.859	1.496	0.000	4.718
Area	2.993	0.182	1.000	4.000	2.980	0.222	1.000	4.000

Source: Computed from NBS 2008/2009 & 2010/2011

The mean age of the household head in the second wave was 47.9 years, with a standard deviation of 15.68. This indicates that there was no substantial variation in age within the data set. However, the difference between the minimum and maximum values (range) was relatively high. Age is an important variable as it reflects the level of farming experience a household head may have accumulated, which could influence technical efficiency. The analysis also revealed that households spent an average of 27.26 hours per week on off-farm work in the first wave. This is equivalent to approximately 4 days per month per person dedicated to off-farm activities.

6.2. Production Functions Estimates

Following the estimation of the unrestricted Cobb-Douglas production function, the analytical findings are presented in Table 2. The results show that the log-likelihood ratio is highly significant. The coefficient for the log of capital, which includes the value of pesticides and machinery, was positive and highly significant at the 1% level. This indicates that increased expenditure on improved seeds, proper use of pesticides, and machinery is likely to enhance farm output. Similarly, an increase in the area under production was also significant, with a positive coefficient at the 1% level. This suggests that farm size under cultivation played a critical role in determining production levels during the study period, particularly in a context of low usage of improved inputs, as is the case in Tanzania. These findings align with those of Lien et al. (2013), who, when estimating a Translog production function, found that land had the largest elasticity value—four times the elasticity of labor and twice the elasticity of machinery and materials. This led their study to conclude that total grain production heavily depends on farm size.

The coefficient for the log of labor was positive and significant at the 5% level. This confirms that farm production remains a labor-intensive activity, with low levels of mechanization in most cases. This is likely to be so due to limited household incomes and a lack of access to credit. A similar observation was made by IFPRI (2013, Ma et al., 2022), which reported that labor had the highest elasticity value for maize production, indicating that labor input is a key determinant of agricultural output. IFPRI also concluded that most farmers in Uganda relied heavily on family labor for agricultural production and that the insignificant coefficients for capital and land in their study could be attributed to low levels of input usage.

Lastly, the coefficient for the predicted log of off-farm hours had a positive value but was not statistically significant. This contrasts with the findings of Lien et al. (2010), who reported that the coefficient for off-farm hours was significant.

Table 2: Production function based on a Cobb-Douglass Production Function

Variable	Coefficient	P-Value
Log area	0.5995574*	0.00
Logfert	-0.0195455	0.67
Loglab	0.1568709*	0.01
Logmapest	0.2663149*	0.00
Pre_log_off	0.0666616	0.37
Sq_Pre_log_off	-0.0112919	0.54
Age	0.000136	0.88
Education	0.0047672	0.59
Hhsize	-0.007669	0.50
Farm_Specific_off	-0.1085825	0.28
Farm_Sp_Sq	0.4140741**	0.03
Conc	0.3349664	0.50
/mu	1.370323	0.73
Eta	0	
Instigma2	-0.5215083	0.74
Ilgtgamma	1.532474	0.40
Sigma2	0.5936245	
Gamma	0.822368	
Sigma_u2	0.4881778	
sigma_v2	0.1054467	

Source: Estimation of Panel data generated from NBS (2008/09 and 2010/11). Estimates are significant at ***P<O.10, **P<0.05 and *P<0.0. A negative sign on a variable indicates a positive impact of efficiency.

The effect of off-farm work on farm technical efficiency was determined using the same equation, consistent with the approach used by Battese and Coelli (1995) for jointly estimating the stochastic frontier and technical efficiency. The signs of the parameters indicated the direction of their effects on efficiency levels, where a negative parameter signified a positive effect on efficiency (Lien et al., 2010). The results showed that the farm-specific off-farm hours variable had a positive sign but was not statistically significant. Therefore, it was not possible to draw any definitive conclusions about the effect of this variable on farm technical efficiency. In other words, there was no evidence to support the argument that rural households' participation in off-farm work had either a negative or positive effect on farm technical efficiency (Lien et al., 2010).

However, the log of the squared farm-specific off-farm hours displayed a positive sign and was statistically significant at the 5% level. This finding suggests that increasing labor hours allocated to off-farm work decreased the level of farm technical efficiency. As a result, the null hypothesis, that is, increasing participation in off-farm work reduces the level of technical efficiency, was accepted. This finding contrasts with earlier studies (Lien et al., 2010; Bagi, 1984; Chavas et al., 2005), which reported no significant effect of off-farm work on technical efficiency. It also opposes the study by Pfeiffer et al. (2009), which observed a slight increase in technical efficiency associated with increased engagement in off-farm employment.

7. Conclusion and Recommendation

The study focused on examining how off-farm work participation by rural households affects farm technical efficiency. This research involved the estimation of panel data generated from two cross-sectional surveys of the LSMS (wave 1&2). The effect of off-farm work on farm technical efficiency was determined by estimating the farm production function, using a Stochastic Frontier Analysis (SFA) approach. The findings revealed that the squared term of farm-specific off-farm hours had a positive and highly significant coefficient. This indicates that increased participation in off-farm work negatively affects the level of farm technical efficiency. In other words, as farmers allocate more time to off-farm activities, their ability to effectively manage their farms declines.

These results suggest that policies aimed at improving farm productivity should consider the potential trade-off between off-farm work and farm management. It may be necessary to ensure synergy in the design and implementation of policies targeting rural areas to balance the competing demands of off-farm work and farm productivity. This study could be extended through a dynamic analysis to explore how rural households transact over a longer period, beyond the scope of the two waves considered in this research.

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