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Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

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To cite this article: Mensah Tawiah Cobbinah, Gideon Danso-Abbeam & Abiodun A. Ogundeji (2023) Access to mutual labour support in agriculture: Implications for maize productivity and efficiency of farmers in northern Ghana, Agrekon, 62:1, 61-79, DOI: 10.1080/03031853.2022.2156898

To link to this article: https://doi.org/10.1080/03031853.2022.2156898

Published online: 01 Feb 2023.

AGREKON
2023, VOL. 62, NO. 1, 61–79
https://doi.org/10.1080/03031853.2022.2156898

Access to mutual labour support in agriculture: Implications for maize productivity and efficiency of farmers in northern Ghana

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ABSTRACT
Access to cheap labour affects Ghanaian smallholder farmers significantly. Such access can be enhanced through mutual labour support. However, it has become necessary to explore how this form of collective action affects farmers' productivity and efficiency. In this study, the impact of access to mutual labour support on productivity and technical efficiency was estimated using data collected from 592 smallholder maize farmers in Northern Ghana. The study uses a translog stochastic production frontier model, while accounting for sample selection bias that may emanate from both observable and unobservable household characteristics. Farmers with access to mutual labour support are significantly more productive and technically efficient than those without, with mean technical efficiency in the range of 0.62–0.71 for farmers with access to mutual labour support and 0.55–0.60 for those without access. Sex, education, spraying machine ownership, farm size, extension visits, access to credit, and membership of farmer-based organisation are significant determinants of access to mutual labour support. Policies to help farmer groups and extension agents promote mutual labour support accessibility among farmers are recommended.

ARTICLE HISTORY
Received 17 November 2022
Accepted 2 December 2022

KEYWORDS
Mutual labour support; stochastic frontier model; selectivity bias; technical efficiency; Violin plot

JEL CODE
Q12

1. Introduction

For most poor people in Sub-Saharan Africa (SSA), agriculture remains their primary source of employment and income (Jayne and Sanchez 2021). Therefore, raising the rate of growth in agricultural productivity would result in sustainable poverty reduction (Gassner et al. 2019). Furthermore, empirical evidence shows that, in developing countries, productivity growth in agriculture is much more effective in reducing poverty than productivity growth in other sectors (Christiaensen, Demery, and Kuhl 2011; Tiffin and Irz 2006). Similarly, agricultural productivity growth aids in releasing skilled workers to other sectors for long-term economic growth (Alvarez-Cuadrado and Poschke 2011). By contrast, most SSA countries are experiencing an odd development pattern where skilled workers leave agriculture to work in other sectors while agricultural productivity stays low (Emerick 2018; Gollin, Lagakos, and Waugh 2011). This phenomenon coupled with an aging workforce due to youth disinterest in agriculture continues to be a challenge that affects agricultural productivity growth in the region (Mabe et al. 2021; Jayne, Yeboah, and Henry 2017).

There have also been claims of low agricultural labour productivity in the region. McCullough (2017) revealed that, in six SSA countries, workers were 3.4 times more productive outside of agriculture than in it. Consequently, there has been an increased interest in exploring methods for

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improving labour access and labour productivity in agriculture. Again, McCullough (2017) noted that labour productivity can be improved through technological gains and capital accumulation or by moving labour out of less-productive activities and into more-productive activities. When there is insufficient capital to either trade-off or substitute human labour for capital and labour-saving technologies, farmers, on the other hand, seek mutual (communal, exchange, cooperative, or joint) labour support (Van der Ploeg and Long 2019). Mutual labour support (MLS) is the primary type of collective activity organised by farmer-based organisations or smallholder cooperatives in developing countries (Sugden et al. 2021; Salifu et al. 2012).

Studies have shown that access to “cheap” labour for timely farm preparation and planting (Tripathi et al. 2021) and technology adoption (Nkegbe and Shankar 2014) can be enhanced through MLS. However, a deeper understanding of how this form of collective action affects farmers’ productivity and efficiency is required. This study contributes to the empirical literature in two ways. First, it examines the impact of access to MLS on farmers’ productivity and efficiency. Second, it tackles potential biases caused by observed and unobserved factors, which are challenges in an observational study of farmers’ decisions to access MLS. The individual’s risk preference, perceived resource endowment, trust, and commitment to the group may affect his access to MLS. Unobserved factors like these can lead to erroneous assessments of the farmer’s efficiency. To address this previously unaccounted phenomenon, a stochastic frontier model with correction for sample selection is used to estimate farmers’ productivity and efficiency. In Ghana, researchers have looked into the impact of technology adoption (Abdulai, Zakariah, and Donkoh 2018), credit access (Missiame, Nyikal, and Irungu 2021; Siaw et al. 2020; Martey et al. 2019; Nkegbe 2018; Abdallah 2016), irrigation adoption (Azumah, Donkoh, and Awuni 2019), participation in off-farm income (Danso-Abbeam, Abban, and Donkoh 2017), farmer-based organisation (Abdul-Rahaman and Abdulai 2018), and agricultural value chain mentorship programmes (Martey et al. 2015) on the technical efficiency of farmers, using different approaches. For example, Danso-Abbeam, Abban, and Donkoh (2017) and Abdallah (2016) included the predicted, rather than the actual values of the selection (treatment) as an additional regressor in the technical inefficiency model. Martey et al. (2019) incorporated propensity score matching (PSM) in the stochastic frontier model to correct observed bias in the technical efficiency of farmers. Missiame, Nyikal, and Irungu (2021) combined the stochastic frontier model with endogenous switching regression to analyze farmers’ technical efficiency, while Siaw et al. (2020) employed an instrumental variable approach and the stochastic frontier analysis method for this purpose. By contrast, Azumah, Donkoh, and Awuni (2019) and Abdul-Rahaman and Abdulai (2018) combined the propensity score matching (PSM) technique with Greene’s (2010) sample selection stochastic frontier model to correct observed and unobserved biases in farmers’ technical efficiency. Though these studies are theoretically relevant, they failed to analyze the impact of access to MLS on maize farmers’ productivity and efficiency in Ghana. To address these lacunae, we set the following hypotheses.

H_1: Access to mutual labour support has a significantly positive influence on the productivity of maize farmers in northern Ghana

H_2: Access to mutual labour support has a positive impact on technical efficiency of maize farmers in northern Ghana.

2. Methods

2.1 Data

This study uses primary data collected from 592 maize farmers in the Northern, Savannah, Northeast, Upper East, and Upper West regions of Ghana. Put together, these regions have 55 districts, 16 in the Northern region, 7 in the Savannah region, 6 in the Northeast region, 15 in Upper East region, and 11 in the Upper West region. The area has established maize producers, but is relatively dry, with a single rainy season that begins in May and ends in October (Ministry of Food and Agriculture 2021). We employed a multistage sampling procedure to select the respondents. In the first stage, we purposively selected ten districts, two from each of the five regions where MLS is largely practiced. In the second stage, 22 communities were also randomly selected from the selected districts. In the final stage, we randomly selected around 28 farmers from each community. In all, 624 maize farmers were selected for the study, according to Yamane (1967), as follows (Equation 1):

$$n = \frac{N}{1 + N(e)^2} = \frac{490,569}{1 + 490,569(0.04)^2} = 624.20 \tag{1}$$

where n is the sample size, N is the population size (490,569) obtained from the Ghana Living Standard Survey round seven (GLSS 7), and e is the margin of error (0.04). The sample size is approximated to 592 because 32 questionnaires were unanswered. We conducted a quantitative survey using a structured questionnaire to collect data from maize farmers in northern Ghana.

2.2 Variable description

In this study, the term mutual labour support(MLS) refers to a labour-sharing arrangement where a group of farmers provides labour to a fellow farmer in rotation until all group members have received the same services in a timely manner. This form of collective labour is conducted in an organised group (cooperatives, relatives, friends, and neighbour). The group has a specific amount of time (number of days) to work on each participant's farm so that they do not miss the right planting, weeding, or harvesting time. MLS allows each member to have his or her farm planted, weeded, or harvested within time and escape the risks of searching for agricultural labour in farming communities, especially in a time when every farmer requires labour for the same activity. Access to MLS enables farmers to acquire the services of a large number of labourers and reduce the cash cost of labour. Furthermore, it ensures that seeds and chemical inputs are used efficiently, which may boost maize farmers' productivity and efficiency. Failure to reciprocate the same help on a colleague's farm when needed attracts money that the group executives insist as compensation for the same services that would have been performed in kind. Otherwise, the farmer is barred from receiving labour services in subsequent seasons. Access to MLS is the selection variable. It is dummy coded one (1) if a farmer received collective labour on his or her maize farm during planting, weeding, and harvesting in a sequential manner and zero (0) otherwise.

Sex is a dummy variable, which is coded as 1 if the farmer is a male and 0 if the farmer is a female. Compared to women, men have greater influence on decision-making and labour allocation to the farm business. We anticipate that male farmers will be more likely to access MLS and become more technically efficient. Age is a continuous variable that is measured by the number of years of the farmer at the time of the survey. We anticipate a negative link between the age and farmers' efficiency, but a positive relationship between age and MLS. Older farmers have a greater wealth of farming knowledge, expertise, and resources for boosting technical efficiency than younger farmers. However, elderly or aged farmers have less energy to conduct difficult work and, as a result, are more inclined to participate in MLS. Education is a dummy variable that is coded as 1 if the farmer can read and write and 0 if he or she cannot. We expect education to positively influence access to MLS and farmers' efficiency since it enhances one's knowledge and ability to read, understand and appreciate the benefits of MLS or adopting improved technologies.

Farmer role in decision-making in the household is a dummy variable, which is coded as 1 if farmer makes production and marketing decision that impacts the farm without consulting any household member and 0 if otherwise. Household size is generally akin to labour availability for the operation of farm activities. It is measured by the number of people eating from the same pot. Farmers with larger household sizes may be able to use family labour for farming operations without accessing MLS. Non-farm job is a dummy variable coded as 1 if the farmer is engaged in non-agricultural activities such as trade in non-agricultural commodities, craftsmanship, and teaching, among others. Non-farm job is a source of income that may be used to hire labour. Hence, we expect a positive relationship between non-farm job and access to MLS.

Phone is a dummy variable, which is coded as 1 if the farmer has a mobile phone and 0 if not. Farmers used their mobile phones to make and receive calls and information about group activities, including MLS, from colleague farmers. A sprayer is used to control weeds without the need for hand weeding. Farmers who have a sprayer may require less labour for weed and pest control and, as a result, are less likely to participate in MLS. Sprayer is a dummy variable that is coded as 1 if the farmer has a sprayer and 0 if not. Crop diversification is a continuous variable that is measured by the number of crops the farmer cultivated in the farming seasons. Growing more crops requires more labour, which can be obtained through MLS.

Farmer-based organisations (FBO) help farmers to access inputs, including labour for production activities. FBO membership is a dummy variable that is coded as 1 if the farmer belongs to an FBO and 0 if otherwise. FBO membership is one way by which farmers obtain MLS. As a result, FBO membership is likely to be endogenous since farmers' decision to join FBO may correlate with the erroneous term in the MLS model. To address the potential endogeneity of FBO membership, we used the Wooldridge (2015). The FBO membership variable represents the dependent variable and is expressed as a function of specific variables, together with an instrument, in the control function model. We derived the generalised residual of FBO membership in the auxiliary probit model, which was subsequently incorporated in the main (structural) model (Equation 2) together with FBO membership. Extension is a continuous variable that is measured by the number of extension visits a farmer received on his or her maize farm in the farming season. Access to extension services allows farmers to learn about the benefits of collective actions, including MLS. Credit is a dummy variable that is coded as 1 if the farmer accessed credit in the 2020/2021 cropping season and 0 if otherwise. Credit gives farmers the financial means to purchase labour, without the need for MLS. Distance is a continuous variable that is measured by the number of kilometres from the farmer's house to the farm. In maize production, input variables include farm size, labour, seed, fertiliser, and insecticides. Farm size is the quantity of land that is committed to maize production. Labour is the number of adults employed for farming activities. Seed is the quantity of maize seed sown per hectare. Fertiliser is the quantity of inorganic fertiliser applied per hectare of maize farm. Pesticide is the quantity of weedicides and insecticides applied per hectare of maize farm. Farm size is measured in hectare (ha), while labour is measured in man-days. Pesticide is measured in litres, while fertiliser and seed are measured in kilogram (kg). Table 1 describes the variables used for the study.

2.3 Econometric strategy

2.3.1 Sample selection stochastic frontier production model

In this study, we employ a stochastic production frontier (SPF) model with correction for sample selection to analyze the impact of access to MLS on farmers' productivity and efficiency. This unconventional SPF model incorporates the Heckman two-stage and propensity score matching (PSM) techniques to deal with unobserved and observed sample selection biases in farmers' TE estimates. Bravo-Ureta, Greene, and Solís (2012) outline seven steps to estimating the sample selection corrected SPF model. The first step estimates a standard SF production function for the unmatched samples by including the selection variable as an additional variable. The second step estimates separate standard SF production functions for unmatched subgroups, while the third step estimates two separate sample selection SF production functions for the unmatched subgroups. This analysis is a correction for unobserved heterogeneity. Here, a binary probit model is used to generate an inverse Mills ratio (IMR), which enters the SF model as an additional variable. The significance of the coefficient associated with the IMR indicates the presence of selectivity bias in unobservable. The fourth step uses a PSM to obtain the matched samples. The first step of the PSM is to predict the propensity score, which is equal to the probability of receiving treatment, considering both treated and

Table 1. Description of variables used for the study.

Variable	Description	Measurement
Sex	Sex of farmer	1 if farmer is a male; 0 otherwise
Age	Age of farmer	Years
Education	Education of farmer	1 if farmer can read and write; 0 otherwise
Decision-making	Farmer role in decision-making in the household	1 if farmer makes production and marketing decision that impacts the farm without consulting any household member; 0 otherwise
Household size	Number of people eating from the same pot	Number of people
Non-farm job	Participation in non-farm job	1 if farmer participates in a non-farm job; 0 otherwise
Phone	Ownership of mobile phone	1 if farmer owns a phone; 0 otherwise
Sprayer	Ownership of spraying machine	1 if farmer owns a sprayer; 0 otherwise
Crop diversification	Total number of crops cultivated	Number of crops
FBO membership	Membership of farmer-based organisations (FBO)	1 if farmer belongs to FBO; 0 otherwise
Extension	Extension visits received by the maize farmer per year	Number of visits
Credit	Farmer access to credit in 2020/ 2021 cropping season	1 if the farmer accessed credit; 0 otherwise
Distance	Distance from house-to-farm	Kilometres
Farm size	Total land area under cultivation	Hectare
Labour	Quantity of people employed for maize production	Man-days
Fertiliser	Quantity of fertiliser employed for maize production	Kilogram
Seed	Quantity of maize seed sown	Kilogram
Pesticide	Quantity of pesticide employed for maize production	Litres

untreated groups based on a given set of predetermined covariates, using a binary choice model (Cameron and Trivedi 2005). This step is followed by imposing the common support region, which is the area within the minimum and maximum propensity scores of treated and comparison groups, respectively (Caliendo and Kopeinig 2008). After matching, we repeated steps one (1) to three (3) for the matched samples. The estimated technical efficiency scores for the treated and control groups were compared using the t-test.

The sample selection stochastic frontier model follows this framework:

$$d_i^*(d_i > 0) = \alpha_0 + x_i'\alpha + e_i\text{: Selection model} \tag{2}$$

$$\ln Y_i = \beta_0 + \sum_{i=1}^{n} \ln X_i\beta + \varepsilon_i\text{: SPF model} \tag{3}$$

where $d_i$is the latent variable representing the propensity to access mutual labour support, $\alpha$is a vector of unknown parameters to be estimated, x_i is a vector of explanatory variables explaining farmers' access to mutual labour support, ande_i is the error term. Note that farmers' decision to MLS is analyzed using the theory of utility maximisation. The theory states that a farmer will access MLS (U_0) only if his level of satisfaction in MLS (U_1) is greater or equal to the level of satisfaction he derives from not accessing (U_0).

The SF production model has a production function and efficiency term. The production function shows the relationship between yield (Y_i) and (β)(v_i)$\varepsilon_i\varepsilon_i = v_i - u_i$ inputs. v_i is any random variation or statistical noise in yield that is outside the farmers' control. u_i represents inefficiency (yield loss) due to variations in farmers' environment. The efficiency component is generated by factors within the control of farmers (e.g., demographic and socioeconomic, farm-specific, institutional, and nonphysical factors).

The error structure is given as follows:

$$\varepsilon_i = v_i - u_i \tag{4}$$

where $u_i \sim N(0,\ 1)$

$v_i = \sigma_v V_i$, where $V_i \sim N(0,\ 1)$

$(e_i,\ v_i) \sim N(0,\ 0), (1,\ \rho\sigma_v,\ \sigma_v^2)$ for $d = 1$

The estimator in the model above is such that e_i is conditional on v_i as follows:

$$e_i|v_i = \rho v + h \tag{5}$$

where $h \sim N[0, (1 - \rho^2)]$, and $h$is independent of v_i

The selection variable is jointly estimated as:

$$d_i^*|v_i = x_i'\alpha + \rho v_i + h, d_i = 1\ (d_i^* > 0|v_i) \tag{6}$$

and the probability of the selection variable is:

$$\text{Prob}[d_i = 1 \quad or \quad 0|x_i, v_i] = \phi\left[(2d - 1)\left(\frac{x'_i\alpha + \rho v_i}{1 - \rho^2}\right)\right] \tag{7}$$

The sample is considered into two parts. For the selected observation $d = 1$, the condition on v_i and the joint density for Y_i and d_i is the product of the marginals.

$$f(Y_i, d_i = 1|X_i, x_i, v_i) = f(Y_i|X_i, v_i)\text{Prob}(d_i = 1|x_i, v_i) \tag{9}$$

The first part is $Y_i|X_i, v_i = (X'_i\beta + \delta_v v) - u$, where u_i is the truncation at zero of a standard normal variable with a standard deviation of δ_{u_i}. The conditioned density is given by

$$f(Y_i|X_i, v_i) = \tfrac{2}{\delta_u}\phi\left(\frac{(X'_i\beta + \delta_v v_i) - Y_i}{\delta_u}\right), (X_i'\beta + \delta_v v_i) - Y_i > 0 \tag{10}$$

Hence, the joint density function is given as

$$f(Y_i, d_i = 1|X_i, x_i, v_i) = \tfrac{2}{\delta_u}\phi\left(\frac{(X'_i\beta + \delta_v v_i) - Y_i}{\delta_u}\right)\varphi\left(\frac{x'_i\alpha + \rho v_i}{\sqrt{1 - \rho^2}}\right) \tag{11}$$

The simulated log-likelihood is given by:

$$LogL_s = \sum_i \log\frac{1}{R}\sum\nolimits_{r=1}^{R}\left\{d_i\left[\tfrac{2}{\delta_u}\phi\left(\frac{(X'_i\beta + \delta_v v_i) - Y_i}{\delta_u}\right)\varphi\left(\frac{x'_i\alpha + \rho v_{ir}}{\sqrt{1 - \rho^2}}\right)\right] + (1 - d_i)\left[\varphi\left(\frac{-x'_i\alpha - \rho v_{ir}}{\sqrt{1 - \rho^2}}\right)\right]\right\} \tag{12}$$

The technical efficiency (TE) is calculated as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X'_i\beta)e^{(v_i - u_i)}}{f(X'_i\beta)e^{(v_i)}} = e^{(-u_i)} \tag{13}$$

where $Y_i =$ observed yield and $Y_i^* =$ frontier yield.

2.3.2 Empirical models

The production frontier estimates are computed using the Translog SPF model. Following Coelli et al. (2003), the translog production function, which nests the Cobb-Douglas, can be written as.

$$\ln Y_i = \beta_0 \sum_{j=1}^{5} \beta_{jk} \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{5}\sum_{j=1}^{5}\beta_{ik}\ln X_{ij}\ln X_{ik} + \sum_{j=1}^{2}\gamma D_i + \sum_{j=1}^{1}\varphi_j Z_i + v_i - u_i \tag{14}$$

whereY_i is the yield of maize, X_i is the quantities of inputs and associated parameters(β), and is $Z_i$the selection variable.

3. Results and discussion

3.1 Descriptive statistics

Table 2 presents summary statistics for the variables of this study for both the unmatched and matched samples. For the unmatched sample, the pooled farmers are, on average, 43 years and predominantly male (56%). The results imply that most farmers are aging but economically active in maize production. The proportion (56%) of male farmers in the current study is nearly the same as in rural Savannah (54%), according to the Ghana Living Standard Survey 7 (GLSS 7) report. Men are better able than women to grow maize because they have the resources to do so.

On average, there are approximately seven members per household, which is a significant source of labour for production (Fischer and Qaim 2012). By contrast, there are more educated farmers and larger household sizes than in the GLSS 7 report. More than half of them had attained formal education (65%), are members of farmer group (55%), and owned phones (68%), which imply that most farmers have what it takes to seek information and make informed production decisions. About 53% have spraying machines.

On average, the farmers own smaller farms (1.64 hectares) and grow few crops (1.58/season), which implies that the average maize farmer in this study is a smallholder[1] and less diversified. Less than 40% of the farmers have access to credit (32%) and non-farm employment (38%), implying that most farmers do not have access to credit and non-farm income to acquire resources and use them judiciously to increase productivity (Abdallah 2016). In Ghana, only 4.62% of the deposit money banks' loans went to agriculture in 2020 (Ministry of Food and Agriculture 2021), which implies a lack of credit for farmers. The mean extension visit is 1.85 per season. The results imply that farmers have limited extension services.

For the unmatched sample, we observe significant mean differences between farmers with access to MLS and those without access for all factors, except quantity of labour and pesticides. In Table 2, most farmers with access to MLS are women who are significantly older than those without access and have more crops grown on large acreages. Furthermore, most farmers with access to MLS have phones, extension services, credits, and non-farm jobs than those without access. By contrast, most farmers with access to MLS do not have formal education. For the matched sample, we observe no significant differences between farmers with access to MLS and those without access for all factors. In the common support graph in Figure 1, we found that the pooled observations were reduced after implementing the matching technique (Bravo-Ureta, Greene, and Solís 2012).

We also conducted the standardised bias test to determine the balance of covariate distribution between farmers with access to MLS and those without access. For brevity, we present the overall mean bias of the standardised bias test rather than the detailed standardised mean difference between farmers with access to MLS and those without access for all covariates. The results show that the overall mean bias is significantly reduced from 34.3–8.1 after matching. The current results imply that the covariate distribution is balanced (identical) across treatments (Zhang et al. 2019). The matched sample is obtained by implementing a 1-to-1 nearest neighbour without a replacement matching technique.

3.2 Determinants of farmers' access to MLS

Table 3 shows the logit model estimates of the factors impacting farmers' access to mutual labour support (MLS). We performed Archer and Lemeshow χ^2 and receiver operating curve (ROC) tests to determine the level of calibration and predictive power of the logit model. The results imply that the model is well calibrated and has high predictive power. The Wald χ^2 (242.43) is also found to be

Table 2. Descriptive statistics of the sample's characteristics.

	Unmatched data							Matched data				
	Pooled		Access Farmers		No access Farmers			Access Farmers		No access Farmers		
Variable	Mean	SD	Mean	SD	Mean	SD	Test of means	Mean	SD	Mean	SD	Test of means
Sex (1 = male)	0.56	0.50	0.52	0.50	0.60	0.49	−1.96**	0.52	0.50	0.51	0.49	0.35
Age (years)	42.93	10.27	44.73	10.47	41.28	9.81	4.14***	44.67	10.53	44.78	9.81	−0.14
Education (1 = read and write)	0.65	0.48	0.58	0.49	0.70	0.46	−2.98***	0.59	0.49	0.58	0.46	0.13
Household size (no. of people)	7.32	3.34	7.38	3.82	7.27	2.94	0.39	7.35	3.84	7.55	2.94	−0.63
Non-farm job (1 = doing non-farm work)	0.38	0.49	0.44	0.50	0.32	0.47	2.82***	0.43	0.50	0.44	0.47	−0.34
Phone (1 = owns phone)	0.68	0.47	0.81	0.40	0.54	0.50	7.2***	0.80	0.39	0.83	0.50	−0.76
Sprayer (1 = owns sprayer)	0.53	0.50	0.47	0.50	0.59	0.49	−3.00**	0.47	0.50	0.46	0.49	0.38
Crop diversification (no. of crops cultivated)	1.58	0.74	1.58	0.88	1.25	0.54	5.50***	1.57	0.88	1.50	0.54	1.14
FBO membership (1 = member)	0.55	0.36	0.60	0.50	0.45	0.41	7.89***	0.56	0.46	0.52	0.21	0.73
Extension (no. of extension visits)	1.85	2.32	2.52	2.97	1.24	1.21	6.97***	2.10	2.88	1.86	1.21	1.42
Credit (1 = access)	0.32	0.47	0.19	0.39	0.44	0.50	−6.90***	0.19	0.39	0.16	0.50	0.80
Farm size (hectares)	1.64	1.49	1.87	1.86	1.44	0.98	3.52***	1.86	1.88	1.62	0.97	1.50
Observations	592		284		392			279		305		

Note*: SD denotes standard deviation; Legends *** and ** show 1% and 5% significant levels, respectively,*
Source*: Field data, 2022*

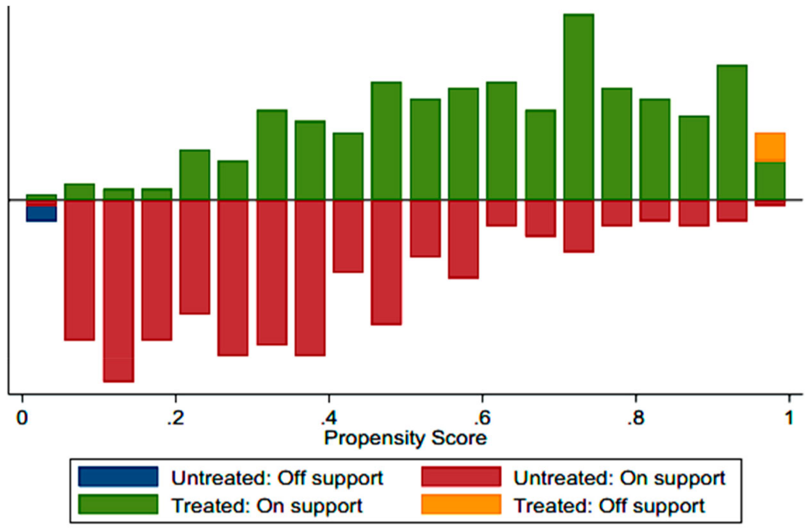

Figure 1. Common support graph after the nearest neighbour, Source: Field data, 2021.

significant at the 1% probability level, which implies that the model fits reasonably well. Each significant covariate is interpreted in light of the ceteris paribus assumption.

Sex has a negative significant marginal effect (−0.2863) on farmers' access to MLS, indicating that women are 28.63% more likely than men to access MLS. Women are less likely to have access to both family and hired labour because of their low economic and social status, which increases their odds of accessing MLS. In most traditional settings, women perform labour in their husbands farms (Ankrah, Freeman, and Afful 2020). Hence, mutual labour becomes a key solution to labour requirement problem, particularly for women who lack the time and physical and financial muscle to work on their farms or hire labour. Education decreases the probability of accessing MLS. The results imply

Table 3. Estimate of the probit model using the unmatched pooled sample.

Variable	Coefficient		Marginal effects	
	Estimate	S.E.	Estimate	S.E.
Sex	−0.7341***	0.2235	−0.2863***	0.0833
Age	0.0099	0.0072	0.0040	0.0029
Education	−0.3521***	0.1344	−0.1397***	0.0527
Household size	0.0008	0.0179	0.0003	0.0071
Phone	0.2239	0.2214	0.0890	0.0874
Non-farm job	−0.1776	0.2454	−0.0707	0.0973
Sprayer	−0.5746***	0.1305	−0.2261***	0.0499
Farm size	0.0608***	0.0216	0.0242***	0.0086
Crop diversification	0.1297	0.1142	0.0517	0.0456
Extension	0.3355***	0.0539	0.1338***	0.0215
Credit	−0.2706*	0.1480	−0.1074*	0.0582
FBO	3.9184**	1.8212	0.7311***	0.0959
FBO residual	−2.5071	1.8212	−1.0000	0.7264
Constant	−1.1530	0.3496		
Observations	592			
Wald χ^2 (12)	242.43			
Prob $>\chi^2$	0.0000			
Pseudo R^2	0.2958			
Receiver operating curve (ROC)	0.8565			
Archer and Lemeshow goodness of fit	0.236			

*Legends: ***, **, and * denote 1%, 5%, and 10% significance levels, respectively; S.E. is the standard error, and M.E. is marginal effects.*
Source: *Field data, 2021*

that the uneducated farmers have a 13.97% likelihood of accessing MLS. Educated farmers are more likely to take up non-farm employment, which may result in a shortage of labour for farming. Although we anticipated that the lost-labour effect of formal education would favour farmers' access to MLS, the findings reveal the opposite. Educated farmers are more likely to take up non-agricultural jobs and are less likely to reciprocate the same labour on a colleague's farm.

Phone use is significant and has a marginal effect of 0.2261, indicating that farmers using phones are more (22.61%) likely to access MLS. The results imply that farmers may use phones to access mutual labour support. Farmers with phones tend to have a ready means of communication, allowing them to arrange for mutual labour support. The marginal effect of farm size is significant and positive (0.0242), implying that a unit increase in farm size would result in a 2.42% increase in the likelihood of accessing MLS. The result implies that farmers who have larger farms are more likely to access mutual labour support, probably due to the correspondingly higher labour and capital requirements. Farmers who have larger farms need a lot of labour in their farm operations, which eventually stimulates them to access MLS.

Spraying machine ownership has a negative significant marginal effect (−0.2261), implying that farmers with no spraying machines have a 22.61% probability of accessing MLS. Farmers can eliminate labour-intensive weed and pest management practices by using spraying equipment. Membership in farmer-based organisation also has a significant positive marginal effect (7311) on the likelihood of accessing MLS. The results show that farmers in farmer-based organisation (FBO) are 73.11% more likely to access MLS. The results imply farmer groups are important channels by which farmers can mobilise and exchange labour for maize production. Olagunju et al. (2021) also showed that farmers who are FBO members use more labour than non-members, which may be due to their increased access to MLS. However, the coefficient of the FBO residual is not significant. This finding implies that farmers' access to MLS is determined exogenously rather than endogenously by their membership in the FBO. Extension visit has a positive marginal effect (0.1338), suggesting that farmers who have extension services are more (13.38%) likely to access MLS. The results imply that extension agents assist farmers in gaining access to MLS. Farmers' chances of accessing MLS are increased by the knowledge that extension agents provide them with on the benefits of collective action in farming. Access to credit also has a significant marginal negative effect (0.1074) on the likelihood of accessing MLS. The results imply that farmers' probability is reduced by 10.74% of accessing MLS if they have credit. Access to credit may be used to hire labour for farm activities, as reported by Abdallah (2016).

3.3 Production frontier estimates

This section shows the estimates of both the standard and sample selection SPF models for the matched and unmatched samples. Tables 4a and 4b present the SPF model results of the factors influencing maize productivity for the unmatched and matched samples. The results were obtained using the seven steps described by Bravo-Ureta, Greene, and Solís (2012). Following the authors, we estimated a single model for the pooled sample and separate models for the sub-samples (access and no access categories). The following likelihood ratio (LR) test formula ($LR = -2 \times [\ln Lp - (\ln Lm + \ln Lc)$), where $\ln Lp$, $\ln Lm$, and $\ln Lc$ represent the log-likelihood function values obtained from the pooled model, the access model, and the no access model was used to test the null hypothesis that the single (pooled) model is an adequate representation of the data than the separate models. The calculated LR values of 29.58 and 33.28 for the pooled model in both the unmatched and matched samples are statistically significant. As a result, we reject the null hypothesis and conclude that the separate models for farmers with access to MLS and those without access are superior to a single model for the pooled sample. The same result was found in Olagunju et al. (2021).

Another LR test was conducted to determine the appropriateness of the two functional forms (Cobb-Douglas and Translog). Following the calculated LR values of 88.35 and 92.13 in the pooled

Table 4a. SPF results of factors influencing maize productivity for the unmatched samples.

	Standard SPF function						Sample selection SPF function			
	Pooled		Access		No access		Access		No access	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
lnlabour	0.167***	0.063	0.209***	0.079	−0.204	0.181	0.208***	0.077	−0.209	0.180
lnfertilizer	0.151***	0.039	0.148***	0.057	0.143**	0.063	0.144**	0.056	0.170***	0.063
lnseed	−0.023	0.04	0.070	0.055	−0.165**	0.066	0.083	0.055	−0.173***	0.065
lnpesticide	0.0002	0.035	0.007	0.047	−0.091	0.063	−0.003	0.047	−0.069	0.063
$0.5 \times \text{lnlabour}^2$	0.069	0.045	0.052	0.06	−0.173	0.137	0.049	0.059	−0.156	0.135
$0.5 \times \text{lnfertilizer}^2$	−0.104***	0.021	−0.104***	0.036	−0.096***	0.026	−0.105***	0.035	−0.093***	0.026
$0.5 \times \text{lnseed}^2$	−0.053***	0.017	−0.007	0.024	−0.122***	0.023	0.001	0.023	−0.119***	0.023
$0.5 \times \text{lnpesticide}^2$	−0.036*	0.022	−0.018	0.034	−0.063**	0.029	−0.026	0.033	−0.053*	0.029
lnlabour × lnfertilizer	−0.004	0.052	−0.035	0.07	−0.005	0.088	−0.039	0.068	0.004	0.086
lnlabour × lnseed	0.043	0.027	0.055*	0.031	0.032	0.077	0.055*	0.030	0.014	0.076
Lnlabour × lnpesticide	−0.003	0.033	0.004	0.039	−0.134	0.09	0.003	0.038	−0.125	0.089
lnfertilizer × lnpesticide	0.021	0.021	−0.024	0.031	0.054*	0.03	−0.027	0.031	0.060**	0.029
lnfertilizer × lnseed	0.053**	0.022	0.045	0.033	0.069**	0.03	0.043	0.032	0.071**	0.030
lnpesticide × lnseed	0.018	0.015	0.037*	0.021	−0.011	0.025	0.037*	0.021	−0.014	0.025
MLS	0.182***	0.061								
Constant	0.691***	0.085	0.717***	0.128	0.780***	0.109	0.621***	0.109	0.880***	0.106
Sigma^2 (σ^2)	0.924***	0.099	0.806***	0.162	0.987***	0.123				
Gamma (γ)	1.563***	0.111	1.238***	0.222	2.101***	0.115				
σ_u							0.698***	0.121	0.888***	0.095
σ_v							0.558***	0.055	0.422***	0.051
RHO (w,v)							0.189**	0.095	−0.211***	0.080
Returns to scale	0.299		0.439		−0.766		0.423		−0.692	
Observations	592		284		308		284		308	

*Legends:***, **, and * denote 1%, 5%, and 10% significance levels, respectively; S.E. is the standard errors*
Source: *Field data, 2021*

Table 4b. SPF model results of factors influencing maize productivity for the matched samples.

	Standard SPF function						Sample selection SPF function			
	Pooled		Access		No access		Access		No access	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
lnlabour	0.165***	0.063	0.185**	0.08	−0.201	0.181	0.193**	0.078	−0.209	0.181
lnfertilizer	0.152***	0.039	0.155***	0.057	0.148**	0.064	0.147***	0.057	0.168***	0.064
lnseed	−0.027	0.04	0.072	0.055	−0.173***	0.066	0.091	0.056	−0.184***	0.066
lnpesticide	−0.003	0.035	−0.004	0.048	−0.084	0.063	−0.011	0.047	−0.066	0.063
0.5×lnlabour^2	0.078*	0.046	0.085	0.061	−0.162	0.139	0.068	0.060	−0.159	0.135
0.5×lnfertilizer^2	−0.099***	0.022	−0.090**	0.037	−0.094***	0.026	−0.090**	0.036	−0.091***	0.026
0.5×lnseed^2	−0.055***	0.017	−0.003	0.024	−0.129	0.023	−0.003	0.023	−0.128***	0.023
0.5×lnpesticide^2	−0.033	0.022	−0.009	0.034	−0.057*	0.029	−0.005	0.033	−0.051*	0.291
lnlabour × lnfertilizer	−0.018	0.052	−0.077	0.071	−0.009	0.088	−0.077	0.071	−0.002	0.087
lnlabour × lnseed	0.049*	0.027	0.071**	0.031	0.032	0.076	0.072**	0.031	0.025	0.076
Lnlabour × lnpesticide	0.003	0.033	0.024	0.039	−0.138	0.09	0.019	0.039	−0.127	0.090
lnfertilizer × lnpesticide	0.015	0.021	−0.041	0.032	0.055*	0.030	−0.049	0.032	0.063**	0.030
lnfertilizer × lnseed	0.050**	0.022	0.034	0.033	0.071**	0.030	0.034	0.032	0.069**	0.030
lnpesticide × lnseed	0.019	0.016	0.039*	0.021	−0.007	0.025	0.039*	0.021	−0.010	0.025
MLS	0.197***	0.062								
Constant	0.663***	0.086	0.671***	0.129	0.771***	0.108	0.507***	0.124	0.865***	0.110
Sigma^2 (σ^2)	0.924***	0.100	0.806***	0.158	0.981***	0.123				
Gamma (γ)	1.561***	0.111	1.261***	0.214	2.096***	0.115				
σ_u							0.680***	0.173	0.890***	0.083
σ_v							0.561***	0.071	0.423***	0.048
RHO (w,v)							0.214**	0.103	−0.175**	0.087
RTS	0.296		0.441		−0.748		0.428		−0.702	
Observations	584		279		305		305		279	

*Legends:***, **, and * denote 1%, 5%, and 10% significance levels, respectively; S.E. is the standard errors*
Source: *Field data, 2021*

model for both the unmatched and matched samples, the null hypothesis (H_o:$\beta_{ij} = 0$) is rejected, meaning that the Translog SPF function fits the data better than the Cobb-Douglas SPF function. We also concur that the translog SPF function is a more flexible functional form than the Cobb-Douglas SPF function, which assumes constant returns to scale (RTS) and accounts for the interactions between variables (Wassihun, Koye, and Koye 2019). As a result, we estimated a Translog SPF function because it fits our data better than the Cobb-Douglas SPF function. The Translog SPF was used by Abdul-Rahaman, Issahaku, and Zereyesus (2021) and Wassihun, Koye, and Koye (2019).

In Tables 4a and 4b, we present the partial elasticities of the conventional inputs variables, as well as the RTS, variance parameters, and selection bias parameter (RHO) for both unmatched and matched samples. All variables are mean-corrected and logarithmically transformed. In all cases, fertiliser and the square of fertiliser have a positive and significant effect on maize yield. This result is consistent with that of Abdul-Rahaman, Issahaku, and Zereyesus (2021). Due to nutrient depletion and climate change, most soils in Africa today are low in fertility, making fertiliser application essential to increasing maize yield. In Ghana, the Planting for Food and Jobs (PFJ) government input subsidy programme has increased the fertiliser application rate from 8 to 20 kg/ha (Ministry of Food and Agriculture 2020), resuling in a significant improvement in maize yields (Asante and Bawa-kyillenuo 2021). The estimated partial elasticity of labour is positive and significant for the pooled and the access samples, but insignificant in the no access sample. This result implies that farmers with access to MLS may not have labour challenges, which enable them to increase their maize yield. Bravo-Ureta, Greene, and Solís (2012) also revealed a significant positive effect of labour on output. Seed has a significant and negative effect on maize yield, which is consistent with Chiona, Kalinda, and Tembo (2014). This result implies that farmers may not be using the recommended amount of seeds.

The sum of all the partial elasticities is less than one, meaning that all SPF models show decreasing RTS. The result is in line with Wassihun, Koye, and Koye (2019) and Bravo-Ureta, Greene, and Solís (2012). Generally, farming among low-resource groups is often marked by decreasing returns to scale. To account for farmers' access to MLS and to confirm the potential sample selection problem suggested by Bravo-Ureta, Greene, and Solís (2012), we included the binary variable (MLS) in the pooled models. The MLS variable is statistically significant in the pooled models, indicating a significant difference in yield between farmers who have access to MLS and those without access.

In Table 5, we present the performance of MLS on maize productivity by comparing the predicted frontier yields between farmers with access to MLS and those without access.

From the results, maize productivity in all cases increases after accounting for sample selection bias due to unobserved and observed factors. However, the maize productivity gaps in all cases widen after accounting for sample selection biases to unobserved and observed factors. These results imply that access to MLS contributes significantly to increasing maize productivity in northern

Table 5. Predicted frontier yield after correcting for biases.

	Standard SPF model			Sample selection SPF model		
Samples	Mean	Min	Max	Mean	Min	Max
Unmatched sample						
Access	3.71	0.26	5.98	3.85	0.26	5.98
No access	2.64	0.24	4.01	2.66	0.24	4.01
Differential (%)	40.5***	8.00	49.1	44.4***	8. 0	49.1
Matched sample						
Access	3.84	0.26	6.11	3.90	0.28	6.42
No access	2.65	0.24	4.11	2.67	0.26	4.18
Differential (%)	44.9***	8.0	48.66	46.1***	0.00	53.59

*Legends *** shows a 1% significance level*
Source: *Field data, 2021*

Ghana. In particular, farmers with access to MLS have 46.1% higher productivity than those without access. For this reason, we computed the selection bias correction term (RHO) to ensure that the results are free from unobserved heterogeneity. In all sample SPF models, RHO is found to be significant, which implies that TE differentials owing to access to MLS are unbiased and consistent. In all cases, the productivity and TE differentials between farmers with access to MLS and those without access are statistically significant.

The aforementioned findings have three primary implications. First, it can be seen that implementing the matching technique and accounting for sample selection increases TE values for farmers with access to MLS and those without. This result implies TE scores would have been underestimated and misleading for policymakers and other potential users of the findings if selection bias from both the observed and unobserved factors was not adequately addressed. Second, after accounting for both the observed and unobserved biases, the efficiency gap between farmers with access to MLS and those without widens, contradicting the results of Bravo-Ureta, Greene, and Solís (2012). Third, while access to MLS increases farmers' TE, it does not eliminate technical inefficiency in maize production. There are still substantial technical inefficiencies (0.29-38) among farmers with access to MLS, which reduce their potential maize yield by 29-38% even after accounting for all biases due to unobserved and observed factors. By instinct, the observed technical inefficiency in maize production could be due to differences in the quantity and quality of MLS. Apart from being inadequate, the composition of MLS can be gender biased or it may include a non-employable population such as children and the aged. For this reason, further research is needed to examine how the quality of MLS affects farmers' efficiency.

3.4 Determinants of maize technical efficiency

In Table 6, we provide alternative factors for reducing the technical inefficiency in maize production. From the results, decision-making role, extension visits, and access to credit have a significant and negative effect on maize farmers' technical inefficiencies, while farm size and house-to-farm distance have a significant and positive influence. The results imply that technical inefficiency in maize production was reduced for farmers with a higher decision-making position in the household, extension visits, credits, shorter home-to-farm distance, and smaller farm sizes. Credit and extension services are important policy variables for increasing farmers' efficiency in maize production. Farmers with access to credit are better able to access expensive efficiency-enhancing technologies like hybrid

Table 6. Sources of maize farmers' technical inefficiency from the matched sample.

Variable	Coeff.	S.E.
Sex	−0.0305	0.0201
Age	−0.0009	0.0009
Decision-making	−0.0594***	0.0212
Education	0.0087	0.0173
Household size	0.0011	0.0022
Non-farm employment	0.0195	0.0169
Farm size	0.0040**	0.0020
Sprayer	−0.0294*	0.0163
Extension	−0.0326*	0.0181
Credit	−0.0389**	0.0187
FBO membership	0.0289	0.0224
Distance	0.0003**	0.0001
Constant	0.7369	0.0450
var(e.TE_CM)	0.0361	0.0021
Observations	584	
F(12, 572);*p*-value	2.72;0.001	
Pseudo R-square	0.1121	

*Legends ***, **, and * shows 1%, 5%, and 10% significance levels, respectively*
Source*: Field data, 2021*

seed and fertiliser, which makes it a significant contributor to technical efficiency (Chiona, Kalinda, and Tembo 2014). Chiona, Kalinda, and Tembo (2014) further revealed that access to extension has a sizable favourable effect on technical efficiency because it helps farmers learn about suitable farming methods and technologies.

3.5 Implications of access to MLS for maize production and technical efficiency

This section presents both the standard and bias-corrected TE scores of farmers with access to MLS and those without access. The standard TE and bias-corrected TE scores were computed using the standard SPF model and sample selection correction SPF model. Note that when access to the MLS variable is neither random nor exogenous, the sample selection correction SPF model produces unbiased and consistent estimates of the TE than the default (standard) SPF model since the former accounts for the sample selection (unobserved heterogeneity) problem. The results are obtained using both the unmatched and matched samples.[2]

Before examining how farmers' access to MLS affects inefficiency, it is important to assess whether an inefficiency problem exists. As shown in Tables 4a and 4b above, the Gamma (γ) estimates in all models are statistically significant, prompting us to reject the null hypothesis (H_0:$\gamma = 0$) that there is no inefficiency problem. The result means that technical inefficiency is stochastic and contributes significantly to the observed maize yield variability, rendering the SPF model superior to the ordinary least squares (OLS) estimator. The same result is revealed by Abdul-Rahaman, Issahaku, and Zereyesus (2021), Olagunju et al. (2021), Wassihun, Koye, and Koye (2019), and Bravo-Ureta, Greene, and Solís (2012). Once the inefficiency problem is confirmed, we find it important to discuss the role that farmers' access to MLS plays in eliminating technical inefficiencies in maize production.

The standard TE results are shown in the first, second, and third columns, while the bias-corrected TE results are shown in the fourth, fifth, and sixth columns of Table 7. In addition, we computed the Epanechnikov kernel density plot (Figure 2a) and Violin plot (Figure 2b) to show the distribution of bias-corrected TE of farmers with access to MLS and those without access after implementing the matching technique. The density curve with yellow and green filled areas in Figure 2a shows the bias-corrected TE of farmers with access to MLS and those without access, respectively.

In Figure 2b, the green rectangle represents the inner quartile range, which holds 50% of maize farmers' TE. In addition, the mean and median TE values are denoted by the blue dot and red bold line, respectively. From the two graphs, we observe that the distributions of TE scores differ between farmers with access to MLS and those without access. Generally, farmers with access to MLS have distributional plots that are closer to the standard normal distribution function than those without access. In addition, the median TE in the inner quartile range of the Violin plots appears

Table 7. Technical efficiency scores

Sample	Standard stochastic frontier production function			Sample selection stochastic frontier production function		
	Mean	SD	Test of means	Mean	SD	Test of Means
Unmatched sample						
Pooled	0.59	0.18				
Access	0.62	0.13	4.79***	0.69	0.11	3.58***
No access	0.56	0.18		0.58	0.15	
Differential (%)	10.7			15.5		
Matched sample						
Pooled	0.58	0.15				
Access	0.62	0.13	4.53***	0.71	0.60	6.00***
No access	0.55	0.17		0.09	0.14	
Differential (%)	12.7			18.3		

*Legends *** shows a 1% significance level*
Source: *Field data, 2021*

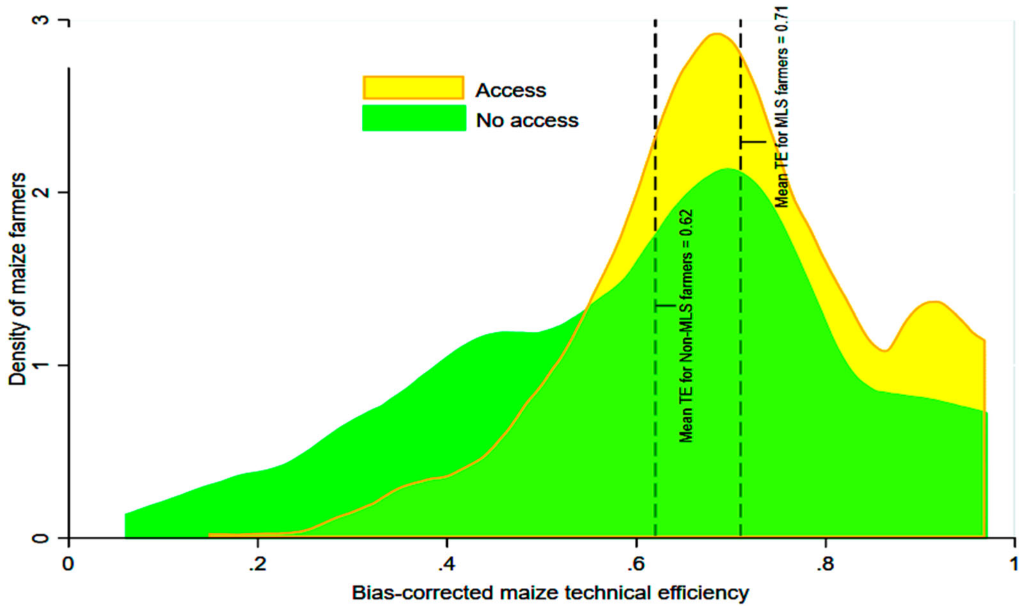

Figure 2a. Epanechnikov kernel density plot, Source: Field data, 2021.

to be close, but the mean TE between farmers with access to MLS and those without access differ significantly. These results are reinforced by Table 7 below, which presents the mean TE for the two groups.

Farmers with access to MLS are technically more efficient than those without access. The beneficial effects of MLS on technical efficiency and productivity may be attributable to the fact that cooperative labour-sharing methods allow farmers to plant on time to prevent crop failure in climate-sensitive agriculture (Mohammed, Baffour, and Rahaman 2021). According to Nkegbe and Shankar (2014), mutual labour sharing encourages smallholders to embrace more improved technologies, which boosts production and efficiency. Relatedly, Mohammed and Abdulai (2022) revealed a significant positive impact of egocentric networks on farmers' technical efficiency in Ghana, and Olagunju et al. (2021) revealed a significant positive impact of cooperative membership on maize

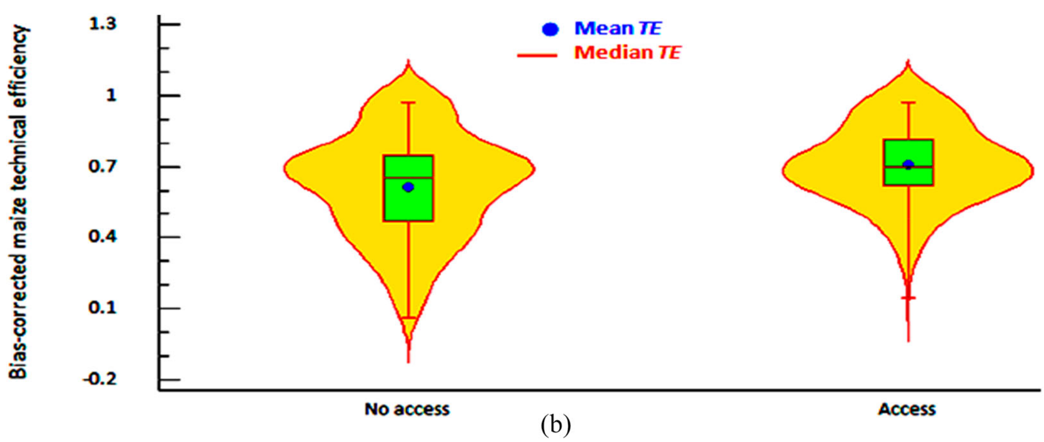

Figure 2b. Violin plot, Source: Field data, 2021.

technical efficiency in Nigeria. The result is also consistent with Llones et al. (2022) who revealed that participation in collective action improves the production of efficiency of irrigated rice farmers in Northern Thailand. The study demonstrates that farmer-to-farmer relationships or social networks are crucial for improving farmers' efficiency in developing countries. Nonetheless, the mean TE in the current study is still lower than those found in most studies (Kwawu, Sarpong, and Agyire-Tettey 2022; Abdulai, Zakariah, and Donkoh 2018; Aravindakshan et al. 2018; Olagunja et al. 2021). On average, the standard TE before and after implementing the matching technique is 0.62 (SD = 0.13) for farmers with access to MLS and 0.56 (SD = 0.18) and 0.53 (0.17) for those without access, indicating that the former is 10.7-12.7% technically more efficient than the latter. Similarly, the mean bias-corrected TE before and after implementing the matching technique is 0.69 (SD = 0.11) and 0.71 (SD = 0.09) for farmers with access to MLS and 0.58 (SD = 0.15) and 0.60 (SD = 0.14) for those without access, implying that the former is 15.5-18.3% technically more efficient than the latter group. As presented above, the TE values for farmers with access to MLS have smaller SD than it is for those without, indicating that the TE values of the former are more homogeneous than those of the latter.

4. Conclusion

In this study, we provide evidence of the impact of MLS on maize productivity and the technical efficiency of farmers in northern Ghana. We employed both standard and sample selection translog stochastic production frontier (SPF) models with the propensity score matching technique to calculate bias- and bias-corrected frontier productivity and technical efficiency. Using cross-sectional data, we show that access to MLS plays a significant role in the productivity and technical efficiency of farmers, but it does not eliminate technical inefficiency in maize production. We observed that technical inefficiency accounts for about one-third of the yield loss in maize among farmers with access to MLS. Following the results, the technical efficiency scores would have been underestimated and misleading for policymakers and other potential users of the findings if selection bias from both the observed and unobserved factors was not adequately addressed. The study demonstrates the importance of access to MLS in improving maize productivity and the technical efficiency of farmers in northern Ghana. Beyond access to MLS, we also showed that the farmer's decision-making position in the household, extension visits, access to credit, distance from house to farm, and farm size act as important factors for improving technical efficiency through the efficient use of inputs. The study may have significant implications for rural agriculture since it would call for policies that promote and strengthen collective action among farmers. Policies are thus, needed to help farmer groups and extension agents promote MLS accessibility among farmers.

Notes

1. Smallholder farmers are those who cultivate less than 2 hectares of land (MoFA 2021).
2. The unmatched sample includes subgroups with unrelated characteristics, while the matched sample includes subgroups with identical characteristics, except for farmers' access to MLS.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abdallah, A.H. 2016. Agricultural credit and technical efficiency in Ghana: is there a nexus? *Agricultural Finance Review* 76, no. 2: 309–24.

Abdulai, S., A. Zakariah, and S.A. Donkoh. 2018. Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. *Cogent Food & Agriculture* 4, no. 1: 1424296.

Abdul-Rahaman, A., and A. Abdulai. 2018. Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. Food Policy 81: 95–105.

Abdul-Rahaman, A., G. Issahaku, and Y.A. Zereyesus. 2021. Improved rice variety adoption and farm production efficiency: Accounting for unobservable selection bias and technology gaps among smallholder farmers in Ghana. *Technology in Society* 64: 101471.

Alvarez-Cuadrado, F., and M. Poschke. 2011. Structural change out of agriculture: Labor push versus labor pull. *American Economic Journal: Macroeconomics* 3, no. 3: 127–58.

Ankrah, D.A., C.Y. Freeman, and A. Afful. 2020. Gendered access to productive resources – evidence from small holder farmers in Awutu Senya West District of Ghana. *Scientific African* 10: e00604.

Aravindakshan, S., F. Rossi, T.S. Amjath-Babu, P.C. Veettil, and T.J. Krupnik. 2018. Application of a bias-corrected meta-frontier approach and an endogenous switching regression to analyze the technical efficiency of conservation tillage for wheat in South Asia. *Journal of Productivity Analysis* 49, no. 2: 153–71.

Asante, F.A., and S. Bawakyillenuo. 2021. Farm-level effects of the 2019 Ghana planting for food and jobs program: An analysis of household survey data. Gssp working PaperWashington, DC, International Food Policy ResearchInstitute.

Azumah, S.B., S.A. Donkoh, and J.A. Awuni. 2019. Correcting for sample selection in stochastic frontier analysis: Insights from rice farmers in Northern Ghana. *Agricultural and Food Economics* 7, no. 1: 1–15.

Bravo-Ureta, B.E., W. Greene, and D. Solís. 2012. Technical efficiency analysis correcting for biases from observed and unobserved variables: An application to a natural resource management project. *Empirical Economics* 43, no. 1: 55–72.

Caliendo, M., and S. Kopeinig. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22, no. 1: 31–72.

Cameron, A.C., and P.K. Trivedi. 2005. *Microeconometrics: Methods and applications*. Cambridge University Press.

Chiona, S., T. Kalinda, and G. Tembo. 2014. Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. *Journal of Agricultural Science* 6, no. 10: 108–18.

Christiaensen, L., L. Demery, and J. Kuhl. 2011. The (evolving) role of agriculture in poverty reduction—An empirical perspective. *Journal of Development Economics* 96, no. 2: 239–54.

Coelli, T., Rahman, S., & Thirtle, C. 2003. A stochastic frontier approach to total factor productivity measurement in Bangladesh crop agriculture, 1961-92. Journal of International Development: The Journal of the Development Studies Association, 15(3), 321–333.

Danso-Abbeam, G., B.A. Abban, and S.A. Donkoh. 2017. Off-farm participation and technical efficiency among smallholder farmers in the Northern Region, Ghana. *Applied Studies in Agribusiness and Commerce* 11, no. 1-2: 35–43.

Emerick, K. 2018. Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics* 135: 488–503.

Fischer, E., and M. Qaim. 2012. Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya. *World Development* 40, no. 6: 1255–68.

Gassner, A., D. Harris, K. Mausch, A. Terheggen, C. Lopes, R.F. Finlayson, and P. Dobie. 2019. Poverty eradication and food security through agriculture in Africa: Rethinking objectives and entry points. *Outlook on Agriculture* 48, no. 4: 309–15.

Gollin, D., D. Lagakos, and M.E. Waugh. 2011. *The agricultural productivity gap in developing countries* (pp. 827–50). Leonard N. Stern School of Business, Department of Economics.

Greene, W. 2010. A stochastic frontier model with correction for sample selection. *Journal of Productivity Analysis* 34, no. 1: 15–24.

Jayne, T.S., and P.A. Sanchez. 2021. Agricultural productivity must improve in sub-Saharan Africa. *Science* 372, no. 6546: 1045–7.

Jayne, T., F.K. Yeboah, and C. Henry. 2017. The future of work in African agriculture trends and drivers of change. International Labour Organization. Working Paper No. 25.

Kwawu, J.D., D.B. Sarpong, and F. Agyire-Tettey. 2022. Technology adoption intensity and technical efficiency of maize farmers in the Techiman municipality of Ghana. *African Journal of Science, Technology, Innovation and Development* 14, no. 2: 532–45.

Kyei, K., and K. Matsui. 2018. Efficiency analysis of rice farmers in the upper east region of Ghana. *In IAFOR International Conference on Sustainability, Energy and Environment in Conference Proceedings*, 1–8.

Llones, C.A., P. Mankeb, U. Wongtragoon, and S. Suwanmaneepong. 2022. Production efficiency and the role of collective actions among irrigated rice farms in Northern Thailand. *International Journal of Agricultural Sustainability*, 1–11.

Mabe, F.N., G. Danso-Abbeam, S.B. Azumah, N.A. Boateng, K.B. Mensah, and E. Boateng. 2021. Drivers of youth in cocoa value chain activities in Ghana. *Journal of Agribusiness in Developing and Emerging Economies* 11, no. 4: 366–78.

Martey, E., W. Dogbe, P.M. Etwire, and A.N. Wiredu. 2015. Impact of farmer mentorship project on farm efficiency and income in rural Ghana. *Journal of Agricultural Science* 7, no. 10: 79–93.

Martey, E., A.N. Wiredu, P.M. Etwire, and J.K. Kuwornu. 2019. The impact of credit on the technical efficiency of maize-producing households in Northern Ghana. *Agricultural Finance Review* 79, no. 3: 304–22.

McCullough, E.B. 2017. Labor productivity and employment gaps in Sub-Saharan Africa. *Food Policy* 67: 133–52.

Missiame, A., R.A. Nyikal, and P. Irungu. 2021. What is the impact of rural bank credit access on the technical efficiency of smallholder cassava farmers in Ghana? An endogenous switching regression analysis. *Heliyon* 7, no. 5: e07102.

Ministry of Food and Agriculture. 2020. 2019 Agricultural Sector Progress Report (APR). Presented at 2020 Agricultural Joint Sector Review (JSR). Ministry of Food and Agriculture. Available at: https://www.mofep.gov.gh/sites/default/files/pbb-estimates/2020/2020-PBB-MoFA.pdf.

Ministry of Food and Agriculture. 2021. Facts and figures: Agriculture in Ghana, 2020. Statistics Research, and Information Directorate of Ministry of Food and Agriculture. Available at: https://srid.mofa.gov.gh/sites/default/files/Agriculture%20In%20Ghana%20Facts%20%26%20Figures_%202020%20FINAL.pdf.

Mohammed, I., P.T. Baffour, and W.A. Rahaman. 2021. Gender differences in earnings rewards to personality traits in wage-employment and self-employment labour markets. *Management and Labour Studies* 46, no. 2: 204–28.

Mohammed, S., and A. Abdulai. 2022. Do Egocentric information networks influence technical efficiency of farmers? Empirical evidence from Ghana. *Journal of Productivity Analysis*, 1–20.

Nkegbe, P.K. 2018. Credit access and technical efficiency of smallholder farmers in Northern Ghana. *Agricultural Finance Review* 78, no. 5: 626–39.

Nkegbe, P.K., and B. Shankar. 2014. Adoption intensity of soil and water conservation practices by smallholders: Evidence from Northern Ghana. *Bio-based and Applied Economics Journal* 3, no. 1050-2016-85757: 159–74.

Olagunju, K.O., A.I. Ogunniyi, Z. Oyetunde-Usman, A.O. Omotayo, and B.A. Awotide. 2021. Does agricultural cooperative membership impact technical efficiency of maize production in Nigeria: An analysis correcting for biases from observed and unobserved attributes. *Plos One* 16, no. 1: e0245426.

Salifu, A., R.L. Funk, M. Keefe, and S. Kolavalli. 2012. Farmer based organizations in Ghana. Retrieved from http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/127387/filename/127598.pdf.

Siaw, A., Y. Jiang, M.A. Twumasi, W. Agbenyo, G. Ntim-Amo, F.O. Danquah, and E.K. Ankrah. 2020. The ripple effect of credit accessibility on the technical efficiency of maize farmers in Ghana. *Agricultural Finance Review* 81, no. 2: 189–203.

Sugden, F., B. Agarwal, S. Leder, P. Saikia, M. Raut, A. Kumar, and D. Ray. 2021. Experiments in farmers' collectives in Eastern India and Nepal: Process, benefits, and challenges. *Journal of Agrarian Change* 21, no. 1: 90–121.

Tiffin, R., and X. Irz. 2006. Is agriculture the engine of growth? *Agricultural Economics* 35, no. 1: 79–89.

Tripathi, A., N. Bharti, S. Sardar, and S. Malik. 2021. COVID-19, disrupted vegetable supply chain and direct marketing: experiences from India. *Journal of Agribusiness in Developing and Emerging Economies*., doi:10.1108/JADEE-04-2021-0095.

Van der Ploeg, J.D., and A. Long. 2019. *Labor, markets, and agricultural production*. CRC Press.

Wassihun, A.N., T.D. Koye, and A.D. Koye. 2019. Analysis of technical efficiency of potato (Solanum tuberosum L.) Production in Chilga District, Amhara national regional state, Ethiopia. *Journal of Economic Structures* 8, no. 1: 1–18.

Wooldridge, J. M. 2015. Control function methods in applied econometrics. Journal of Human Resources, 50, no. 2: 420–445.

Yamane, T. 1967. Statistics, An Introductory Analysis, 1967. New York Harper and Row CO. USA, 213, no. 25.

Zhang, Z., H.J. Kim, G. Lonjon, and Y. Zhu. 2019. Balance diagnostics after propensity score matching. *Annals of Translational Medicine* 7, no. 1: 16–.