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The Impact of Contract Farming on Technical Efficiency in Ethiopia's Smallholder Sesame Production

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ABSTRACT— Ethiopia has been struggling in the international Sesame market due to low productivity. Therefore, contract farming (CF) has been introduced as a new institutional arrangement to improve productivity. The purpose of this paper is to investigate the impact of CF on smallholder's technical efficiency (TE) using cross-sectional data from 122 CF and 261 non-CF sesame farmers in Ethiopia. A data envelopment analysis (DEA) is used to estimate sesame production efficiency. The impact of CF on technical, allocative, and economic efficiency was assessed using propensity score matching (PSM). A Rosenbaum bound approach was used to see to what extent the PSM results is sensitive to hidden bias problem. Based on the DEA result, CF participants have an average TE score of 0.68 and non-CF has 0.56 under constant return to scale. This indicates that to increase TE, CF participants and non-participants can reduce the amount of input use by 32% and 44%, respectively. Farmers can increase TE under variable return to scale by reducing input level on average by 23% and 32% for CF and non-CF, respectively. The AE for CF participants is 0.26, while the non-CF participant has an AE of 0.20. The PSM results revealed that contract farming increases technical efficiency by 11% and economic efficiency by 8.7%. AE is increased by 8% due to CF. Therefore, contract farming can be used as an institutional arrangement to improve production efficiency.

KEYWORDS: Contract farming; DEA; Economic efficiency; Propensity score matching

1. INTRODUCTION

Sesame production and marketing play a substantial role in the Ethiopian economy. It is one of the six priority crops to achieve agricultural commercialization [1,2]. 75% of sesame production is for the export market. Smallholder farmers produce two-third of the total sesame production on their less than 5 ha farmland. The sector has a great deal of contribution in terms of export earnings and employment opportunities for the rural and national economies [1]. Despite having a comparative advantage of cheap labor and growing demand for sesame in the world market, Ethiopia is struggling due to low productivity. Ethiopian sesame faces high competition due to the rise in volume and value of sesame in the world market. Sesame export performance of the country falls from 3rd to 10th [3]. Productivity determines the country's ability to compete on the international market and depends on natural factors, farming efficiency, and access to modern inputs and technologies. Ethiopian sesame has a low average productivity growth rate per annum [4]. Sesame farmland increased by 61.23 % in 2013 due to the growing demand in the international market. But, the total productivity decreased by 27.23 % [5]. Sesame production increased by 27.7 % in 2014/15 [4]. However, this increase in production was to area expansion allocated for sesame productions. The average national sesame productivity is 7qt /ha [6]. Productivity is still far below the country's projected average capacity of 16qt/ha [1]. Lack of modern inputs and technologies, poor post-harvest management, and imperfect market structure for input and output are the main causes of "Lower productivity" [5, 6]. The uses of modern farming techniques can, therefore, double productivity [1]. Considering that most rural household livelihoods depend on agriculture, increasing productivity is crucial in agricultural marketing and alleviating poverty. Priority is given for a sustainable increase in agricultural productivity and agro-industrial development to achieve the millennium development goal in the context of producing more and selling more [7]. Ethiopia's 2010/11- 2014/15 Growth and Transformation Plan (GTP), focuses on high-value marketable crops such as sesame. Including smallholder farmers in the production and marketing of these high-value crops requires a search for functional markets and institutional arrangements [1]

One way of achieving agricultural productivity is by integrating smallholder farmers to modern agricultural supply chains via contract farming. As suggested by Swain (2016), contract farming improves farm efficiency by introducing new technologies, production methods, and optimal allocation of resources to smallholder farmers. It also serves as a road to transforming agriculture in developing countries from subsistence to modern [9]. Linking smallholder farmers with consumers and more industrialized sectors through contract agreements as one of the policy options enables farmers to enjoy trade benefits and can be used as fuel to promote economic development [10]. Considering the importance of sesame to the Ethiopian economy, the objective of this study is to estimate the level of efficiency and to identify the source of inefficiency. It also analyzed the impact of contract farming on production efficiency. Several studies assessed the effect of contract farming on efficiency based on a stochastic frontier analysis (SFA) to determine the efficiency score [8,11,12,13]. However, SFA analysis requires specific production function and distributional assumption. The Misspecification of production function results in biased estimation [14]. Therefore, in this study, a data envelopment analysis (DEA) was used for efficiency score estimation. Unlike SFA, DEA is free from any production function assumption. Since DEA is limited to efficiency score estimation, a statistical hypothesis test on factors that might have a meaningful effect on efficiency is difficult. Therefore, a two-stage analysis technique was used to address the objective. In the first stage, data envelopment analysis (DEA) was implemented to determine the efficiency level. The efficiency score from the DEA analysis is then used as an outcome variable in the second stage to determine the impact of contract farming on efficiency using propensity score matching (PSM).

2. Material and Methods

2.1 Sample size and sampling technique

Cross-sectional data were collected in 2019 from farm households producing organic sesame in Humera where according to Gidey (2018) one third of Ethiopian sesame is generated. The sample size was determined based on Kothari (2004),

$$n = \frac{Z^2 * P(1-p)}{e^2} \qquad (1)$$

$$384 = \frac{1.96 * 0.5(1-0.5)}{0.05^2}$$

Where n is sample size, z represents standard variate at 95% confidence interval, e is the acceptance error and p is the probability of participation. Since the actual proportion of participant is unknown, 0.5 is used for P to get maximum sample size. Primary data was collected from 122 CF participants and 261 non-CF participant organic sesame producing smallholder households using a multistage sampling technique. Humera at the first stage and five sub-districts at the second stage were purposively selected based on the production potential of the area and CF availability. At the third stage, households were grouped into two

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strata, as CF participants and non-CF participants and sample households were randomly selected.

2.2. Empirical model

I. Efficiency analysis: Input Oriented Data envelopment analysis (DEA)

In this study, a DEA method is used to estimate technical efficiency. DEA is a non-parametric linear programming approach to determine the level of efficiency at the production frontier for each decision-making unit (DMU) [16]. It is free of any assumption of a production function; therefore, it is advantageous over avoiding misspecification of production relation. Also, it quantifies the inefficiency source for each DMU. In this study, the factor product relationship is explained by a single output- multiple inputs relationship. An input-oriented DEA analysis provides how much input can be reduced without reducing the current production level [17]. In this input-output relationship, the input variables include labor, land, tractor hour, and seed. The input-oriented technical efficiency is calculated based on a constant return to scale (CRS) and variable return to scale (VRS) assumption. Equation 1 below is based on the CRS assumption [18].

$$\text{Objective: } \min_{\theta,\lambda} \theta$$
$$\text{subject to:}$$
$$X_{ij}\theta - \sum_{i=1}^{m} X_{ij}\lambda_j \geq 0$$
$$\sum_{j=1}^{n} Y_j \lambda_j \geq 0$$
$$\lambda_j \geq 0,$$
$$\text{for } \forall_j, \theta \text{ is unconstrained} \qquad (2)$$

Here xij and yj are respectively inputs and outputs defined earlier; λj is vector of weights of the efficient farms helping in projection of inefficient farms to an efficient frontier (i.e. the distance of inefficient farms from the frontier); θ is an index of farm's technical efficiency ranging between 0 and 1. When the minimization problem model in equation 1 is further constrained by $\sum \lambda_j = 1$ based on Banker, Charnes, & Cooper (1984) , the technical efficiency is decomposed into technical efficiency and scale efficiency

Economic Efficiency: is calculated based on cost minimization problem.

$$\text{Objective: } \min_{x^*_{ij},\lambda_j} C_{ij} \,.\, X^*_{ij}$$
$$\text{subject to:}$$
$$\sum_{j=1}^{n} Y_j \lambda_j - Y_j \geq 0$$
$$X^*_{ij} - \sum_{j=1}^{n} X_{ij}\lambda_j \geq 0$$
$$\lambda_j \geq 0; \text{for } \forall_j \qquad (3)$$

Where θ is the efficiency score, Y_j is the amount of output produced by DMUj, C_{ij} is the price of input i for the j^{th} DMU, X^*_{ij} is cost minimizing vector of input i for DMU_j and the input level that the DMU_j should use to be efficient is indicated by λ.

Allocative efficiency (AE): is achieved when an output is produced at minimum possible cost. It is based on an input price. AE is computed based on the ratio of Economic efficiency (EE) to Technical efficiency (TE)

$$AE = \frac{EE}{TE} \qquad (4)$$

The summary of input used, yield produced, and production cost used in the DEA model are summarized in the Table below.

Table 1. Variables used in the DEA analysis

		Contract participant		Non-participant	
	Description	Mean	Std	Mean	Std
Land size (ha)	Total allocated land for sesame production in hectare	4.38	2.6	2.8	1.4
Land rent per ha	Land price per hectare	2204.24	313.15	2249.38	213.82
Total Labor (hr)	Total family and hired labor hour spent on production	1725.982	2671.92	1508.82	1859.63
Labor cost	Total labor cost per hr.	593.69	907.73	591.28	374.43
Tractor hour (hr)	Total hour spent on land preparation	14.2	18.05	20.52	44.54
Tractor rent	Total cost spent for land preparation	1232.973	823.9469	1660.973	1345.187
Seed (kg)	Amount of sesame seed used in kg	20.99	14.55	15.86	9.61
Seed cost	Seed price per kg	44.27	5.93	46.07	7.24
Yield (qt)	Total amount of sesame produced	25.97	12.72	15.53	7.58
Output price (birr/qt)	Output price per qt	4366.72	526.92	4294.41	430.59

Source: authors 'survey

2.3 Impact of contract farming on efficiency analysis

In this study, the impact of contract farming on production efficiency was assessed using a propensity score matching (PSM) together with Rosenbaum Bounds' sensitivity analysis approach. Rosenbaum & Rubin (1983), introduced propensity score matching to address the selection bias problem in a casual estimate. PSM is based on the assumption that participation is independent of the outcome conditional on household characteristics, and that treatment selection is independent of pretreatment characteristics [21, 22, 23]. A propensity score was calculated using logistic regression to match the treatment (CF participant) with the control group (CF non-participant) on all other dimensions except the intervention. A logit model was used as it provides a consistent parameter estimation and more density mass in the bounds [22, 24]. The variables used to match the contract farming participant with non-participant includes age of the head, sex of the head, education level, family size, years of experience in sesame production, off-farm income, access to credit, access to extension service, distance from the local market, land ownership, and risk behavior of the head. Nearest neighbor matching, radius matching, and Kernel matching were applied. A Kernel matching with a bandwidth of 0.2 was selected to match the participant farmers with the non-participant based on the propensity score. Kernel matching provided a minimum mean bias of 4.4, and a balance in all covariates between a treated and control group was confirmed. After matching, the impact of contract farming on efficiency was assessed by comparing the difference between the participating and non-participating farm households using average treatment effect on the treated (ATT) and average treatment effect (ATE). Adopted from [25, 26],

ATE and ATT is estimated by

$$\mathrm{ATE} = \{\mathrm{E}(\mathrm{Y}_1|\mathrm{X}, \mathrm{T} = 1) - \mathrm{E}(\mathrm{Y}_0|\mathrm{X}, \mathrm{T} = 0)\} \qquad (5)$$

$$\mathrm{ATT} = \mathrm{E}\{\mathrm{E}(\mathrm{Y}_1|\mathrm{X}, \mathrm{T} = 1) - \mathrm{E}(\mathrm{Y}_0|\mathrm{X}, \mathrm{T} = 0)|\mathrm{T} = 1\} \qquad (6)$$

Where Y is efficiency (potential outcome), T represents participation with a value equal to 1 if household participates and 0 otherwise and X represents the explanatory variables. PSM is criticized for not considering an unobserved variable that can simultaneously affect both the treatment and the outcome and give an inaccurate estimation [22, 24, 27]. Therefore, based on Caliendo and Kopenig (2005), a Rosenbaum Bounds approach was used to detect unobserved heterogeneity. Given the equation by Caliendo and Kopenig (2005),

$$P(X_i) = P(D_i = 1|X_i) = F(\beta X_i + \gamma u_i) \quad (6)$$

Where Xi is the observed characteristics for individual i, ui is the unobserved variable and γ is the effect of ui on the participation decision. If unobserved variables do not affect, then γ will be zero.

3. Result and Discussion

3.1 Efficiency analysis result

From both constant returns to scale (CRS) and variable return to scale (VRS) assumptions, farmers engaged in contract farming have higher technical (TE) than their non-participant counterparts. There is a very low average allocative efficiency (AE) and economic efficiency (EE) score for both participants and non-participants.

Table 2. Efficiency score distribution

	CF participant						**Non CF participant**					
score range	<=0.5		0.51-0.99		1		<=0.5		0.51-0.99		1	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
TE (CRS)	14	11.5	103	84.4	5	4.1	81	31.0	173	66.3	7	2.7
TE (VRS)	5	4.1	95	77.9	22	18	39	14.9	190	72.8	32	12.3
AE	102	83.6	20	16.4	0	0	228	87.4	32	12.3	1	0.4
EE	109	89.3	13	10.7	0	0	250	95.8	10	3.8	1	0.4

Source: authors' survey

Out of the total contract participant farmers, 84.42 % have TE (CRS) above 50 %, while 66.28 % of the total non-participants have above 50 % TE (CRS). The AE score result shows that none of the Cf farmers are on the efficiency frontier, and only 0.38% of the non-CF are allocative efficient. 16.39 % and 12.26 % of the participant and non-participant have AE score between 50 %-99% respectively. A lower AE indicates that most farmers produce sesame at a point where their marginal cost is higher than their marginal benefit. Farmers, therefore, need to reduce their production cost by optimum reallocation of resources. The EE shows that sesame production in the study area is inefficient due to both technical and allocative inefficiency.

Table 3. Data envelopment analysis result

	Efficiency score				
Efficiency type	**Participant**		**Non-participant**		
	Mean	Std	Mean	Std	T-test
TE (CRS)	0.685	0.158	0.578	0.159	-6.1587***
TE (VRS)	0.775	0.176	0.712	0.184	-3.2021***
AE	0.267	0.206	0.200	0.205	-2.9236***
EE	0.199	0.183	0.120	0.144	-4.5740***

Source: authors'survey

Those farm households producing sesame under contract farming and on production possibility frontier have a strong TE with zero slack value for all input level use. The high relative efficiency level for participants can be because of farm machinery like a tractor, technical advisory service, and improved inputs provision by the firm. As indicated in Table 3, to achieve TE, participant farmers who produce below the production possibility frontier can cut their input level by 31 % under CRS and 22% under VRS.

Table 4. Source of inefficiency mean comparison

	CF-participants	Non CF-participants
Input used	Mean (Slack value)	Mean (Slack value)
Land (ha)	.034	.021
Labor(hr)	363.50	371.13
Oxen hour(hr)	2.90	8.40
Seed (kg)	.297	.75

Source: authors‘survey

The slack value from the DEA analysis results in Table 4 shows that there are unused input levels in production. Therefore, non-CF farmers can cut hours spent on land preparation by 8hr and the amount of seed they used by 0.75 kg/ha to reduce inefficiency. To increase efficiency, participants and non-participant's farmers can reduce land allocated for sesame production by 0.03 ha and 0.02ha for respectively. Resource allocation decisions can be adjusted based on the return to scale status to reduce production inefficiency. The return to scale implies the average productivity of inputs. As Table 5 below indicates, farmers with smaller land sizes have increasing returns to scale as compared to farmers with relatively large farmland.

Table 5. Return to scale distribution by land size

	Constant return to scale				**Increasing return to scale**				**Decreasing return to scale**			
	CF Participant		CF Non-Participant		CF Participant		CF Non-Participant		CF Participant		CF Non-Participant	
Land size (ha)	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
≤ 2	2	1.6	1	0.4	26	21.3	124	47.5	0	0	8	3.1
2 < X ≤5	2	1.6	6	2.3	40	32.8	95	36.4	27	22.1	21	8.1
5 < X ≤10	1	0.8	0	0	1	0.8	1	0.4	19	15.6	4	1.5
10 < X ≤14	0	0	0	0	1	0.8	0	0	3	2.5	1	0.4
Total	5	4.1	7	2.7	68	55.7	220	84.3	49	40.2	34	13.0

Source: authors‘survey

The results in Table 5 show that 55.74% of contract participants and 84.29 % of non-participants enjoyed an increasing return to scale. Most of the participants and non-participants that produce under increasing return to scale have smaller than 5 ha farmland. Land is the main production resource in agriculture. Therefore, farmers can increase the average productivity of sesame by increasing the scale of production. 40 % of participants and 13% of non-participant's households produced sesame under a decreasing return to scale. As a result, those farmers exhibiting a decreasing return to scale need to reduce the amount of input used to increase average productivity and achieve efficiency.

3.2 Impact of Contract farming on production efficiency

Ten respondents were outside the common support area and excluded from the PSM analysis. After matching, the participants and non-participants become similar in their observed characteristics, which were presumed to have an impact on both participation decisions and efficiency. As a result, a balance in covariates was achieved to estimate the impact of contract farming using PSM.

Propensity score matching result

Table 6. Propensity score matching result on ATE and ATT

	ATT					
Efficiency	Participant	Non- Participant	Difference	Std. Error	T-stat	ATE
TE (CRS)	.68	.56	.12	.020	6.27***	.11
TE (VRS)	.77	.68	.086	.023	3.77***	.074
AE	.27	.19	.08	.030	2.91***	.08
EE	.1986	.11	.09	.021	4.18***	.087

***, ** and * refers to 1%, 5% and 10% significance level, respectively
Source: authors'survey

CF farm households have 12 % and 8.6 % higher TE than non-CF farm households if they produce under CRS and VRS, respectively. The TE, AE, and EE differences between participants and non-participants are significant at 1%. The production of sesame under contract farming has a promising average treatment effect. CF increases TE by 11 % (CRS) and 7.4 % (VRS) at a 1% significance level. Farmers can increase EE by 8.7 % due to contract farming. The positive effect of CF on efficiency is because, in addition to providing input on credit base, the company has its extension agents who make farm visits and provide technical assistance and training to improve production techniques. The company also provides tractor services to farmers for land preparation. Similar results on the positive impact of contract farming on efficiency are reported [8, 11,28, 29, 30]. Farm households have a low level of AE. In addition to the high labor requirements and labor cost for sesame production, inefficiency may be due to poor decision-making by farmers on the allocation of resources. As Chavas et al. (2005), point out that low AE occurs when there is an inefficient distribution of farm labor and non-farm labor. Although the participating farmers incur a higher input cost, they still enjoy positive net revenue due to the high production volume and better prices offered by the firm. Maertens and Vande Velde (2017) have revealed that, although contract farming increased input cost by 30 %, the 13% increase in yield gave farmers a positive net income per ha. Contract farming, therefore, improves EE.

4. Rosenbaum Bounds sensitivity analysis

The Rosenbaum Bounds sensitivity analysis results in Table 8 below confirmed that the unobserved variables have no altering effect on ATT and ATE. The conditional independence assumption for this analysis therefore holds, and we can trust the result that contract farming will increase TE, AE, and EE.

Table 7. Rosenbaum bounds sensitivity analysis result

Treatment	Γ=1	Γ	Maximum p-value
Contract farming on TE (CRS)	>0.00001	6.5	.045
Contract farming on TE (VRS)	>0.001	2	.006
Contract farming on AE	>0.008	6	0.01
Contract farming on EE	>0.00001	4	.029

Source: authors 'survey

The value of Γ varied from 1 - 10 to assess the extent to which the unobserved confounder could affect the PSM result. As Table 7 indicates, the impact of contract farming on TE (VRS) is the least robust against the selection bias problem. But here we must bear in mind that this doesn't mean CF has no significant effect on TE. Rather it indicates that the impact of CF on TE under VRS is susceptible to hidden bias problems if unobserved variables influence participation selection causing the odds ratio of treatment assignment between the participants and non-participants to differ by 2.

5. Conclusion and Recommendation

Both contract farming participant and non-participant farm households have low AE and EE. However, this study found that contract farming significantly increases TE, AE, and EE by 11%, 8%, and 8.7%, respectively. We can, therefore, conclude that introducing CF to non-participants is a better way to improve production efficiency. Non-participants can increase production efficiency with less input if they use the input combination techniques similar to farmers producing on the production possibility frontier. In addition to the inputs used, decision-making on resource allocation and management influences production efficiency. CF participant households have AE of 0.26, and the non-participants have AE of 0.20. To increase AE, farmers can significantly reduce input costs without affecting their current level of production and achieve a least-cost input combination. Based on this study, CF farmers need to reduce the level of labor. Non-participants have to reduce the amount of seed and tractor hours used for land preparation. Therefore, in addition to providing production equipment and inputs, contract firms need to introduce farmers with different input combination techniques to increase efficiency. Although this study revealed a positive impact of contract farming on farm households, the average land size (4.38 ha) of participants is almost twice that of a non-participant (2.8 ha). This indicates that firms tend to have a contract agreement with farmers who have a relatively large farm size. Therefore, the government needs to encourage many large agribusiness firms to have contractual arrangements with smallholder farmers. Otherwise, the exclusion of these farmers from the selection would make Contract farming a questionable development and poverty reduction strategy.

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