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Research article

Assessing the effect of contract farming on sorghum land productivity: An endogenous switching regression approach

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A B S T R A C T

In low-and middle-income countries, contract farming handles agricultural problems facing small-scale growers. This study analyzes the extent to which sorghum productivity can be enhanced under contract farming in Tanzania. Using cross-sectional data from 400 sorghum growers in Tanzania and an endogenous switching regression model, we observed that contract farming significantly improves the productivity of contract farmers compared to non-contract farmers. The findings show a 12 % increase in productivity for contract farmers, while non-contract farmers could potentially increase their productivity by 28 % if they participated in contract farming. Moreover, the study identifies significant variables such as age, off-farm income, location, hired labor, the mix of owned-hired labor, farm size, financial services, household size, gender, experience, and the number of groups as determinants of contract farming participation among sorghum farmers. The results call for policies emphasizing contract farming as a viable approach to improve sorghum productivity, especially for small-scale farmers. Furthermore, policy adjustments matching the specific requirements of farmers in the target area are needed to maximize the positive impact of contract farming, factoring in the heterogeneity among producers.

1. Introduction

1.1. Background information

Agriculture drives most sub-Saharan African economies, including Tanzania, accounting for about 24 % of the Gross Domestic Product (GDP) [1]. Approximately 65 % of the Tanzanian population relies on agriculture as their primary means of livelihood [2]. Despite its contribution, over 90 % of producers, typically smallholder farmers, face several production and marketing challenges [2].

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Moreover, the Government of Tanzania (GoT) and other partners recognize the strategic importance of agriculture, seeking to promote sustainable agriculture and enhance competitiveness, thereby improving productivity, income, food security, and livelihoods.

Sorghum (*Sorghum bicolor* L. Moench) is a highly versatile crop widely grown in East Africa. Its high degree of climate adaptability makes it a dependable crop for many communities, serving various purposes, including food consumption, livestock feed, and beer production. Notably, the sorghum clear beer value chain ranks as the second-highest priority value chain for the commodity, and the crop's utilization in clear beer manufacturing is expected to increase from 37,000 tons annually in 2015 to 69,000 tons by 2025 [3]. Commercial sorghum clear beer production began in East Africa in Uganda around 2002, followed by Kenya in 2004 and Tanzania in 2007 [3,4].

In Tanzania, following the introduction of sorghum-based clear beer products by brewing companies (i.e., Serengeti Brewery Limited (SBL) and Tanzania Brewery Limited (TBL)), brewing companies introduced the Contract Farming (CF) model to guarantee their local sorghum supply at a low cost while also providing farmers with a reliable market [3]. CF addresses unstable markets and limited access to quality inputs, enabling farmers to invest more in production, which improves sorghum productivity. The challenges sorghum farmers face in Tanzania differ geographically: some areas face more significant difficulties in accessing markets due to poor infrastructure, while others may struggle with varying climatic conditions affecting production. Furthermore, challenges differ by the value chain type, where some regions have better integration into commercial supply chains than others [3]. These issues also vary over time, with seasonal fluctuations in demand impacting productivity and market accessibility [4]. The model effectively addresses these region-specific challenges that contribute to low productivity among sorghum farmers, such as limited access to quality seeds and inconsistent agricultural practices among smallholder farmers. CF greatly enhances yields and incomes by providing technical support and market security. In 2020, sorghum was Tanzania's third most important cereal crop, with 650,500 tons, following maize and rice. Smallholder farmers contribute about 601,470 tons to the overall production of the crop in the country [2,5]. Additionally, sorghum is the third most prevalent crop in the semi-arid regions of Tanzania, accounting for approximately 50 % of the country's total commercial sorghum production [6].

CF is credited as a strategy for agricultural transformation by enhancing input use and providing a constant market for farmers [7]. However, CF is not a mandatory arrangement in which all farmers must participate. Abdul-Rahman et al. [8] argue that farmers tend to self-select themselves into agricultural arrangements based on their socioeconomic and institutional characteristics. Therefore, it is crucial to understand what determines CF participation and its impact on farmers. In Tanzania, developing a clear beer value chain based on sorghum is seen as an opportunity for CF to enhance sorghum production and marketing, especially for smallholder farmers whose collective production contribution (92.5 %) is significant [2]. The CF model is expected to drive sorghum farmers' production, encouraging them to adopt improved seeds and implement good practices, resulting in higher yields and increased marketable outputs. However, sorghum production in Tanzania has remained low and subsistent, indicated by a 1.26 tons/ha productivity among sorghum farmers [2].

The lack of information about CF is more noticeable for crops such as sorghum, maize, and rice than common cash crops in Tanzania [9,10]. Bidzakin et al. [7] argue that CF is less efficient for traditional food crop value chains. Moreover, there is limited information regarding the impact of CF on sorghum yield in East Africa, especially in Tanzania [10,11]. It remains unclear whether sorghum brewery CF in Tanzania has increased productivity, and if so, to what extent. Furthermore, the results on the impact of CF on productivity are mixed across value chains and contexts. Some literature [7,12–14] indicate that CF positively contributes to productivity, while also [13,15] report an insignificant association between CF and productivity. Understanding how CF shapes sorghum productivity becomes vital with such variability across value chains and contexts.

Therefore, the objective of this study is to assess whether CF matters for smallholder farmers and how it influences sorghum productivity. The findings will inform policy debates with evidence on how CF can promote productivity. By demonstrating the benefits of CF, particularly for a staple crop like sorghum, this study will contribute to informing policies that promote CF to improve food security, rural livelihoods, and agribusiness linkages. The results could encourage reforms to increase CF adoption, incentivize agribusinesses to engage with smallholder farmers and enhance the institutional support systems essential for CF success. This will benefit both the farmers and the brewing industry by ensuring a reliable supply of local sorghum and fostering sustainability in the sorghum sub-sector.

1.2. Conceptual framework

Many small-scale farmers face major agricultural problems in most African countries, such as a lack of quality inputs and fluctuating market prices [5,10]. CF is proposed to help farmers overcome these challenges by establishing structured relationships between farmers and buyers [7]. The primary form of contracting that sorghum farmers are involved in, in Tanzania is through TBL-facilitated contracts, which offer farmers some benefits that include improved seeds and extension services alongside an assured market for their sorghum produced. These contracts specify production practices, standards of quality, schedules of delivery, and mechanisms of price determination, thus reducing the risks facing farmers by providing secure market access and income stability. CF is instrumental in addressing gaps in input supply, market access, and technical knowledge transfer in Tanzania's agricultural sector [10]. Providing quality inputs and technical support by CF enables farmers to adopt improved practices and invest more in production, leading to increased sorghum yield per hectare (kg/ha), a measure of partial factor productivity. Institutional and socioeconomic factors also shape CF in Tanzania (Appendix 1). These factors may influence sorghum farmers' decisions to participate in CF and its benefits (Fig. 1).

According to Random Utility Theory (RUT), individuals choose an alternative that provides maximum utility. From this perspective, farmers are considered utility maximizers who adopt CF if they perceive that its net benefit, which entails higher productivity and stable income, is greater than the other alternatives [16]. The conceptual framework below illustrates how household, farm, and institutional attributes influence the decision to participate in CF and the resulting productivity. This implies that these institutional and socioeconomic characteristics show the relationship between CF participation and productivity; hence, in assessing the overall impact of CF on smallholder farmers in Tanzania, understanding how these variables shape farmers' decisions and outcomes becomes important. This framework emphasizes the practical role of CF in enhancing farmers' access to input, knowledge, and markets, ultimately leading to improved land productivity.

2. Materials and methods

2.1. Theoretical framework

RUT forms the foundation of this study, confirming that individuals are rational because they tend to choose an alternative that maximizes their utility among others [16]. Farmers are expected to maximize their output and productivity from CF (U_{ijt}) (Equation (2)).

$$\text{MAX } U_i = \text{f(X)} \tag{1}$$

$$U_i^* = U_{ijt} > U_{ikt} \tag{2}$$

Where U^* represents the anticipated benefit from higher utility obtained by engaging in CF (U_{ijt}) rather than not engaging in CF (U_{ikt}). Further, i represents individual, j and k represent alternatives CF and NCF, respectively, while t represents time.

The level of CF involvement that every farmer experiences is not observable, and the utility (U_i^*) obtained is determined by the socioeconomic and institutional characteristics (X_i) of the farmer that may influence their involvement in CF, with an ensemble of parameters that need to be calculated β and the error term ε_i (Equation (3)).

$$U_i^* = \beta X_i + \varepsilon_i \tag{3}$$

As conditions of limited and mutually exclusive options are sustained in CF participation [16], it is then represented as a probability (Equation (4)) and can be estimated by models of binary choices.

$$\Pr\left(Ui < \gamma^{X_i}\right) \tag{4}$$

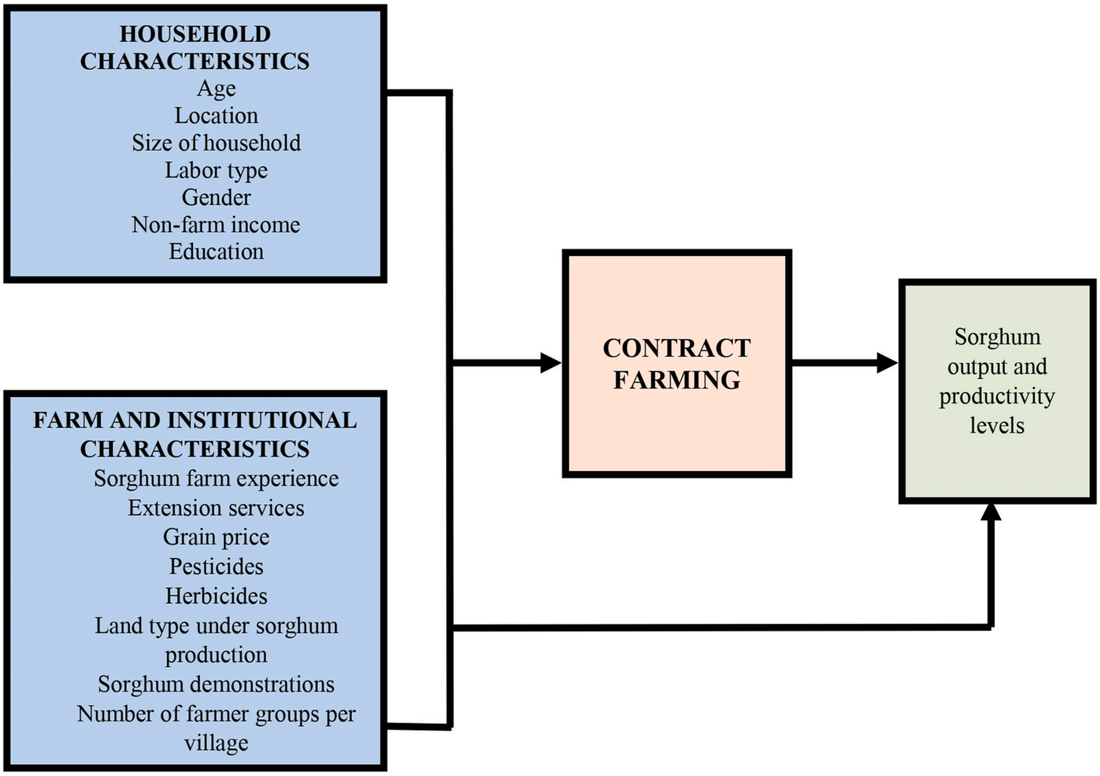

Fig. 1. Conceptual framework.

2.2. Study area and sampling procedure

This research used data collected in 2021 in three distinct areas within Dodoma region, specifically Kongwa, Chamwino, and Mpwapwa districts. The region stands out for its significant sorghum cultivation. According to Ref. [2], during the 2019/2020 season, Dodoma region accounted for 40 % of all sorghum cultivation areas in Tanzania, the highest among sorghum-producing regions.

A multistage sampling approach was employed to select sorghum farmers across six main producing regions: Dodoma, Singida, Shinyanga, Mwanza, Mara, and Songwe. Subsequently, 11 districts were also purposefully chosen based on their significant contribution to sorghum cultivation. A random sampling technique was used to select 768 individuals within these districts. Cochran's formula below was followed in determining the sample size with a margin error of 3.54 %, resulting in a sample size of 768 farmers. The level of precision was chosen for estimates to be as accurate as possible against the available resources for data collection. The formula used is shown below (Equations (5) and (6)):

$$n_0 = \frac{Z^2 . p . (1-p)}{e^2} \tag{5}$$

$$n_0 = \frac{1.96^2 . 0.5 . (1-0.5)}{0.0354^2} \tag{6}$$

$$n_0 = 768 \text{ farmers}$$

Where Z = 1.96 for a 95 % confidence level, p = 0.5 is the assumed population proportion, and e = 0.0354 is the margin of error.

Participants were approached through community meetings facilitated by local leaders, extension officers, and direct farm visits. Farmers were informed about the study's purpose and were invited to participate voluntarily. Data were collected using questionnaires (Appendix 3), with interviews conducted with each farmer individually at village local offices. However, this study focuses exclusively on the subset of 400 smallholder sorghum farmers in Dodoma region with 176 contract farmers (CFs) and 224 non-contract farmers (NCFs). The data from other regions, which lacked CFs, could not be used since it would be impossible to draw meaningful comparisons between the two groups. This could result in biased conclusions about the effect of CF. Consequently, we concentrated our analysis on Dodoma, where we could find a complete representation of CFs and NCFs in the same region, ensuring a robust analysis of the CF dynamics.

The dataset employed in this analysis is the same as that used in our earlier study [17], which analyzed the determinants of farmers' participation in CF. While the study focused explicitly on identifying factors influencing participation decision, this paper extends the analysis by estimating the causal impact of CF participation on land productivity using Endogenous Switching Regression (ESR) and Propensity Score Matching (PSM) models. This distinction reflects that the two papers have different objectives, analytical insights, conclusions, and implications.

2.3. Ethical approval and respondents' consent

This study received approval from the Ethical Review Committee (ERC) of the Department of Technology Transfer and Partnership at the Tanzania Agricultural Research Institute (TARI), under reference number TARI/NAL/TG/T.VOL 1X/189 dated 1/10/2020. The approval followed ethical standards, including maintaining confidentiality, fully informing participants about funding sources and the implications of the findings, and ensuring the fair selection of respondents.

Informed consent was obtained from all participants before data collection, ensuring their involvement in their study and data publication, while maintaining respondent anonymity and responsibly storing any personally identifiable data. Respondents were informed of their right to withdraw from the study at any point. Consent for data publication was also obtained. Because most farmers in this study were illiterate, verbal consent was obtained for both participation and data publication, as the consent form was embedded at the top of the questionnaire. The translated consent statements in the local language were provided to explain the research objectives, details concerning participation, guarantees of confidentiality, and how the publication would occur while anonymity would be maintained. The interviews were only carried out after participants gave consent to participate and publish the data.

2.4. Data analysis

Descriptive statistics were used to analyze the characteristics of CFs and NCFs. The ESR model was adopted to analyze CF's effect on sorghum farmers' productivity. In addition, the PSM model was used to verify the robustness of the results. The simple mean difference in productivity between CFs and NCFs does not account for the confounding effects of unobservable characteristics in analyzing the impact of CF [18,19], thereby demonstrating the reliability of using the ESR and PSM to avoid misleading conclusions. Also [7,20,21], used multiple methods (PSM and ESR) to increase the robustness of their respective findings. The two models are further specified in the following sub-sections. Furthermore, Stata (Statistics and Data), version 14, was used for data analysis.

2.4.1. ESR specification

ESR was developed from Heckman's selection correction model, as noted by Ref. [22]. By treating selectivity as an unobserved variable [23], argues that selection bias is effectively addressed. ESR estimation involves two stages: first, a probit model is estimated, followed by a regression in the second stage. In this study, ESR is used to analyze how CF influences farm productivity as in most agricultural arrangements, like CF, farmers are not randomly selected, thus leading to endogeneity and selectivity problems. Compared to the Heckman model, the ESR approach is preferred since it treats the two farmer groups (CFs and NCFs) as partitioned groups and analyzes the differential responses of the two groups separately [7].

This ESR model is based on certain key assumptions to address the problem of selection bias. First, there is unobserved heterogeneity, where unobservable factors affect farmers' choices to participate in CF and productivity outcomes; this is crucial because these unobserved characteristics can significantly influence both decisions and outcomes, captured through the correlation of error terms in the selection and outcome equations. Second, it uses instrumental variables for exclusion restrictions that affect CF participation without directly impacting productivity. This allows the model to isolate the causal effect of CF participation. For example, valid instruments like the number of groups per village influence the decision to participate without directly affecting productivity, addressing potential confounding factors. Finally, the model allows the computation of counterfactuals to compare actual productivity with hypothetical scenarios, such as estimating what would have occurred had CFs not practiced CF, or vice versa for NCFs. This counterfactual analysis is necessary for understanding the causal impact of CF, adding depth to the model's policy relevance. Together, these assumptions are justified through their ability to address selection bias, ensure proper identification of effects, and provide meaningful insights into the impacts of CF. Studies [7,8,24] have also employed ESR to assess the effect of CF on ginger, rice, and maize farming. The following is a specification of the ESR model (Equations 8 to 17).

It is assumed in RUT that a farmer decides to take part in CF if the anticipated utility from CF is greater than that of not participating in CF, which may be expressed as:

$$U_{\mathrm{CF}} - U_{\mathrm{NCF}} > 0 \tag{7}$$

The probit model can first model the benefit from CF participation by i$^{\text{th}}$ farmer as the selection equation (Equations (8) and (9)):

$$CF_i^* = \gamma Z_i + \mu_i \tag{8}$$

$$\mathrm{CF} = 1 \text{ if } \mathrm{CF}_i^* > 0;\ \mathrm{CF} = 0 \text{ if } \mathrm{CF}_i^* \leq 0 \tag{9}$$

Where Z_i is a vector of various socioeconomic and institutional variables shaping farmers' decision to join CF or not, and μ_i is an error term (Appendix 1). Whether farmers join CF, the observed net benefits are expressed in Equations (10a) and (10b).

$$\textbf{Regime 0}\ (\mathrm{NCF}) : \mathrm{SFP}_{\mathrm{iNCF}} = \mathrm{X_i}\beta_{\mathrm{NCF}} + \varepsilon_{\mathrm{iNCF}}\ \textit{if}\ \ \gamma \mathrm{Z_i} + \mu_i \leq 0 \tag{10a}$$

$$\textbf{Regime 1}\ (\mathrm{CF}) : \mathrm{SFP}_{\mathrm{iCF}} = \mathrm{X_i}\beta_{\mathrm{CF}} + \varepsilon_{\mathrm{iCF}} \text{ if } \gamma \mathrm{Z_i} + \mu_i > 0 \tag{10b}$$

Where $\mathrm{SFP_{iNCF}}$ and $\mathrm{SFP_{iCF}}$ are the outcome variables (sorghum farm productivity) for NCFs and CFs, $\mathrm{X_i}$ is the vector of socioeconomic and institutional factors influencing sorghum productivity among farmers (Appendix 1), and β and Z are estimated parameters.

In addition, the explanatory variables for farmers' decisions regarding CF participation and their productivity were selected based on a range of empirical studies (Appendix 1). These variables were chosen because they are widely recognized in literature as significantly influencing CF involvement and productivity (Appendix 1). Moreover, the Full Information Maximum Likelihood (FIML) method is used to calculate parameters of the probit and regression equations concurrently to obtain consistent standard errors, as it is an efficient estimation method for the ESR approach [22,25]. According to Ref. [26], the problem of estimating the equations separately is resolved by the FIML, which generates heteroscedastic residuals. From the probit stage, estimates such as the inverse Mill's ratio (IMR) (λ_{CF} *and* λ_{NCF}) are employed in the second stage equation to adjust for selection biases. To address selection bias, ESR solves the issue by calculating inverse ratios (λ_{1i} andλ_{0i}) and covariance terms ($\sigma_{1\mu}$*and* $\sigma_{0\mu}$), then includes them as auxiliary regressors in the outcome equations (10a, 10b). Moreover, the three error terms from the probit and ESR equations are assumed to have the following variance-covariance matrix (Equation (11)) and a trivalent normal distribution with mean vector zero.

$$\Omega = \begin{bmatrix} \sigma_{\mu,\mu} & \sigma_{\mu,\varepsilon_1} & \sigma_{\mu,\varepsilon_2} \\ \sigma_{\varepsilon_1,\mu} & \sigma_{\varepsilon_1,\varepsilon_1} & \sigma_{\varepsilon_1,\varepsilon_2} \\ \sigma_{\varepsilon_2,\mu} & \sigma_{\varepsilon_2,\varepsilon_1} & \sigma_{\varepsilon_2,\varepsilon_2} \end{bmatrix} \tag{11}$$

Where $\sigma_{\mu,\mu}$ is the var (μ), $\sigma_{\varepsilon_1,\varepsilon_1}$ is the var (ε_1) and $\sigma_{\varepsilon_2,\varepsilon_2}$ is the var (ε_2), then, $\sigma_{\mu,\varepsilon_1} = \text{cov}\ (\mu_i, \varepsilon_1)$ and $\sigma_{\mu,\varepsilon_2} = \text{cov}\ (\mu_i, \varepsilon_2)$.

The estimation of $\sigma_{\mu,\mu}$ can be scaled and assumed to be equal to 1, and cov ($u_{1,}\varepsilon_2$) is not defined, as two regimes' equations can be observed simultaneously [22]. The correlation of the error terms between the equations is non-zero (corr (μ_i, ε_1) and corr $(\mu_i, \varepsilon_2) \neq 0$), which creates selection bias [22]. Bidzakin et al. and Ma [7,26] claimed that there is selectivity bias if either ρ_{1i} orρ_{0i} deviates significantly from zero. Setboonsang et al. [27] argue that if $\rho_{0i} >$, it indicates negative selection, suggesting that NCFs perform below average, and that CFs would have outperformed NCFs had they not joined CF. Conversely, if $\rho_{0i} < 0$, it indicates positive selection, implying that NCFs perform above average without CF; if CFs had opted not to join CF, their performance would have been less favorable than that of NCFs. Additionally, if $\rho_{1i} > 0$, it indicates positive selection, implying that CFs have above-average performance under CF. If $\rho_{1i} < 0$, it indicates negative selection, suggesting that CFs perform below average under CF and that NCFs would have outperformed CFs had they joined CF.

2.4.2. Treatment effects on farm productivity

[25] argue that ESR estimates indicate the Average Treatment effect on the Treated group (ATT) and the Average Treatment on the Untreated group (ATU). ESR compares the actual productivity of CFs and NCFs as well as in counterfactual situations. We present the outcome variable's conditional expectations in four cases (Equations (12)–(15)).

$$\mathrm{E}(\mathrm{Y}_{iCF}\ |\mathrm{CF}=1)=\mathrm{X}\beta_{iCF}+\lambda_{CF}\ \sigma_{CF\mu} \tag{12}$$

Sorghum farmers who participated in CF (observed)

$$\mathrm{E}(\mathrm{Y}_{iNCF}|\mathrm{CF}=0)=\mathrm{X}\beta_{iNCF}+\lambda_{NCF}\ \sigma_{NCF\mu} \tag{13}$$

Sorghum farmers who did not participate in CF (observed)

$$\mathrm{E}(\mathrm{Y}_{iNCF}\ |\mathrm{CF}=1)=\mathrm{X}\beta_{iCF}+\lambda_{CF}\ \sigma_{NCF\mu} \tag{14}$$

CFs if they did not participate in CF (counterfactual)

$$\mathrm{E}(\mathrm{Y}_{iCF}\ |\mathrm{CF}=0)=\mathrm{X}\beta_{iNCF}+\lambda_{NCF}\ \sigma_{CF\mu} \tag{15}$$

NCFs, if they participated in CF (counterfactual)

The expected productivity of CFs (ATT) is a difference between equations (12) and (14) (Equation (16)).

$$\mathrm{ATT}=\mathrm{E}(Y_{iCF}\ |\mathrm{CF}=1)-\mathrm{E}(Y_{iNCF}\ |\mathrm{CF}=1)=X_i(\beta_{iCF}-\beta_{iNCF})+\lambda_{CF}\ \left(\sigma_{CF\mu}-\sigma_{NCF\mu}\right) \tag{16}$$

Similarly, the expected productivity of a farmer not participating in CF if had participated in CF (ATU) is a difference between equations (13) and (15) (Equation (17)).

$$\mathrm{ATU}=\mathrm{E}(Y_{iCF}\ |\mathrm{CF}=0)-\mathrm{E}(Y_{iNCF}\ |\mathrm{CF}=0)=X_i(\beta_{iCF}-\beta_{iNCF})+\lambda_{NCF}\left(\sigma_{CF\mu}-\sigma_{NCF\mu}\right) \tag{17}$$

Moreover [25], argue that exclusion restriction variable(s) are used as selection instruments to easily identify the ESR. That is, one or more variables must be incorporated into the selection equation but not into the outcome equation. Di Falco and Veronesi [28] contend that it is essential to conduct a falsification test. If the variable is an appropriate selection instrument, it should impact the CF choice, not the outcome. This study uses the number of farmer groups per village as a selection instrument. Further, in the outcome equation, land productivity (kg/ha) is the dependent variable, presented along with other variables used in the ESR estimation (Appendix 1).

2.4.3. The PSM specification

The PSM approach was introduced as a non-parametric technique that compares the observed outcomes of the treatment and the control groups [29]. It is used in impact evaluation studies to analyze the effects of treatments on household welfare and outcomes, whereas self-selection is a problem [7]. Rosenbaum and Rubin [29] argue that inferences about the effects of the treatment involve assumptions about how the treatment would affect those who received a different one. Since PSM estimates alone cannot compute ATT, we find counterfactuals matched to each adopter based on their propensity score generated by a probit or logit model that matches the treatment and control groups. The propensity score is the probability of receiving treatment given the observed characteristics [14].

This study estimated propensity scores using a probit model to analyze CF participation. Three matching techniques, Nearest Neighbor Matching (NNM), Radius Matching (RM), and Kernel-Based Matching (KBM), were then used based on their propensity scores. The most robust outcome was then selected to determine CF's effect on productivity. The PSM estimation is specified as follows (Equations (18)–(22)):

$$ATT=\left(\sum\frac{S_1}{C}=1\right)-\left(\sum\frac{S_0}{C}=1\right) \tag{18}$$

$$ATT=\left(\sum\frac{S_1}{C}=1\right)-\left(\sum\frac{S_0}{C}=0\right) \tag{19}$$

Since equation (16) is non-observable, equation (17) provides a biased estimate of the causal effect of CF participation. To correct for selection bias, we use:

$$ATT=\left(\sum\frac{S_1}{C}=1\right)-\left(\sum\frac{S_0}{C}=1\right) \tag{20}$$

The propensity score is estimated as follows:

$$P(z)=Pr\left(D=\frac{1}{z}\right) \tag{21}$$

Finally, the ATT is computed as shown in Equation (22):

$$ATT = E\left[\frac{S_1}{C} = 1, P(z)\right] - E\left[\frac{S_0}{C} = 1, P(z)\right] \tag{22}$$

Where S_1 represents the outcome for CFs, S_0 represents the outcome for NCFs, C represents CF participation, and z represents socioeconomic and institutional characteristics (Appendix 1).

3. Results

3.1. Socioeconomic and institutional attributes of sorghum farmers

The distribution of CFs and NCFs across different categorical variables is shown in Table 1. The findings show that most CFs were females (56 %). Around 67 % of CFs participated in sorghum demonstration activities, and a significant proportion of CFs (51 %) had better access to off-farm income sources. Furthermore, CFs had greater access to extension services (66 %) compared to NCFs. More CFs were likely to obtain credit (81 %), pesticides (85 %), and herbicides (75 %). CFs (51 %) and NCFs (49 %) primarily relied on a mix of family and hired labor for their farming activities. Additionally, most NCFs (60 %) utilized owned land for sorghum production.

The findings in Table 2 show that CFs had higher productivity, with an average productivity of around 547 kg/ha more than NCFs. The mean difference in grain price indicated that CFs earned, on average, 376.05 Tshs/kg (0.16$) more than NCFs.

As we used the same dataset as [17], some variables reported in Ref. [17] were omitted in this paper for Tables 1 and 2 to avoid redundancy. In this paper, categorical and continuous variables are thus presented to focus on factors influencing productivity outcomes among CFs and NCFs, differentiating the focus of this paper from Ref. [17], which analyzed drivers of CF participation.

3.2. Determinants of productivity among CFs and NCFs

Table 3 presents the estimates for sorghum productivity for CFs and NCFs based on the ESR model. The Wald test is significant at 1 %, indicating the presence of endogeneity and that the ESR model is fit to use. The likelihood ratio test of independence is also significant, suggesting that the selection and outcome equations are independent and should be estimated together. The ESR instrument used is the number of farmer groups per village, and it is confirmed by the falsification test to be a reliable indicator for CF participation but not for productivity. Furthermore, the positive and significant correlation coefficient reflects a positive selection bias. Table 3 also highlights heterogeneity within farmers, with distinct differences in the coefficients of the outcome variables between NCFs and CFs. Among NCFs, sorghum productivity was significantly influenced by owned and rented land, grain price, gender, farm size, and off-farm income, whereas for CFs, owned land, age, household size, and formal education significantly influenced productivity.

Specifically, Table 3 shows that the use of both owned and rented land was linked with a 76 % decrease in productivity. In contrast, being a CF who used owned land for production was associated with a 19 % increase in productivity. For NCFs, a rise in grain price by a unit was associated with a 0.1 % rise in productivity, while for CFs, each additional year of age was linked to a 1 % increase in productivity. Being male was associated with a 30 % rise in productivity for NCFs. Regarding household size, having an extra household member was linked to a 4 % decrease in productivity for CFs. Furthermore, expanding the production area by 1 ha has likely decreased productivity by 11 % for NCFs. Moreover, an additional year of formal education was linked to a 3 % increase in productivity for CFs, and participating in off-farm activities led to a 25 % increase in productivity among NCFs.

3.3. Determinants of CF participation among sorghum farmers

Table 3 further presents the estimates of the factors influencing CF participation. While these estimates are drawn from the first stage of the ESR model, they are included not as the main focus but to provide context on how CF involvement decisions shape the subsequent analysis of CF's effect on land productivity, which is the main objective of this paper. Estimation shows that age, off-farm activity, location, hired labor, the mix of owned-hired labor, farm size, and financial services positively influenced farmers toward CF.

Table 1
Categorical attributes of sorghum farmers (n = 400).

Variables	CFs (%)	NCFs (%)	Chi2
Female	56.16	43.84	13.81***
Sorghum demos (Yes)	67.31	32.69	95.54***
Off-farm income (Yes)	51.23	48.77	13.27***
Extension service (Yes)	66.26	33.74	124.45***
Financial service (Yes)	80.70	19.30	36.34***
Pesticides (Yes)	84.78	15.22	35.09***
Herbicides (Yes)	75.00	25.00	3.18*
Labor (Hired and family)	50.85	49.15	23.51***
Land type (Owned)	40.41	59.59	13.015***

CFs = contract farmers; NCFs = non-contract farmers.
Chi2 values represent the results with significance levels: ***$p < 0.001$, *$p < 0.05$.
Source: Field data

Table 2
Continuous attributes of sorghum farmers (n = 400).

Variables	CFs mean	NCFs mean	t-value
Productivity	1238.64	691.48	7.82***
Grain price	548.30	172.25	12.72***

CFs = contract farmers; NCFs = non-contract farmers.
t-values represent the results of t-tests with significance levels: ***$p < 0.001$.
Source: Field data

In contrast, household size, gender, experience, and number of groups per village negatively influenced CF participation. Table 3 shows that being in Chamwino increased the likelihood of CF by 57 %. The use of hired labor is associated with a 93 % increase in CF participation, while a family and hired labor mix increased involvement in CF by 72 %. Age positively influenced CF engagement, with every additional year increasing the probability of participation by 3 %.

On the contrary, being male decreased the possibility of CF engagement by 29 %. A larger household size decreased the likelihood of participation by 12 %, while an increase in farm size increased the possibility of farmers joining CF by 13 %. In addition, off-farm activity increased the likelihood of CF involvement by 45 %, while access to financial services increased participation by 73 %. Moreover, a higher number of groups per village is associated with a 9 % decrease in CF involvement, and an increase in experience decreased the probability of CF participation by 6 %.

3.4. ESR estimates on the effect of CF on productivity

Findings show that CF positively and significantly influences sorghum productivity. In addition to the mean productivity differences between CFs and NCFs presented in the descriptive statistics (Table 2), the ATT results (Table 4) account for selection bias due to these differences. The causal effect of CF on the productivity of CFs results in a 12 % increase in sorghum productivity. Furthermore, the ATU estimates (Table 4) show that NCFs' productivity would increase by 28 % if they had joined CF. In addition, the ESR's dependent variable is represented as the logarithm of sorghum productivity; thus, the ATT and ATU predictions are provided in logarithmic form.

3.5. PSM estimates on the effect of CF on productivity

Table 5 presents the PSM estimates showing a significant gain in sorghum productivity due to CF in all matching methods. Thus, with consistency across methods, the ATT from the Kernel method is chosen since its estimates are more efficient and less biased. Table 5 demonstrates that CF causes a 12 % increase in sorghum productivity. In addition, the PSM results align with ESR, as they both show a 12 % increase in productivity from CF. This emphasizes that the findings are robust and confirms that CF significantly affects productivity.

4. Discussion

4.1. Determinants of productivity among sorghum farmers

This study confirms CF's positive contribution in improving sorghum farmers' farm yield in Tanzania. The positive selection bias for CFs indicates that more productive farmers are likely to join CF, where high-yielding varieties are provided alongside technical support and financial services. This provides a fundamental implication for the Tanzanian context and beyond, suggesting that CF programs targeting productivity-enhancing interventions among smallholder farmers are essential. However, the productivity gap between NCF and CF suggests the need for supportive policies to address those barriers faced by NCFs. Likewise [7], report the skewed productivity of CFs over the NCFs. Further, NCFs could be more productive and competitive, with improved access to resources like input, credit, extension services, and training.

Low productivity for owned and rented land farms operated by NCFs may indicate poor field management and limited financial access to invest in improved inputs, which calls for improved financial services and farmer training. Rented land could expand farm operations, as supported by Ref. [30]; however, this potential is constrained by resource limitations in rural Tanzania. Conversely, CFs using owned land benefit from direct access to improved seeds, technical support, and financial services. This highlights the importance of support structures through CF schemes. This agrees with [30,31], who argue that land ownership is critical for farmers' productivity. However [32], indicate that land ownership in rural Tanzania remains a challenge. Limited access to land restricts smallholder farmers' ability to scale up production and fully participate in CF. This underscores the need for policy reforms to improve land access and ownership among smallholder farmers, particularly in rural areas. Such interventions would empower farmers to engage more productively in CF, addressing both productivity and market participation challenges while ensuring the long-term sustainability of these initiatives in Tanzania's agricultural sector.

This increase in grain prices incentivizes NCFs to adopt improved technologies, as noted by Ref. [33], while CF with TBL ensures price stability that similarly encourages adoption among CFs. The inability to offer price stability through contracts makes NCFs more responsive to market fluctuation, and higher prices may drive them to adopt innovations that maximize returns. This relationship

Table 3
Endogenous switching regression results on CF effect on farm productivity (n = 400).

Variables	Coef.	Rob Std.Err.
Productivity (NCF)		
Kongwa	−0.008	0.142
Chamwino	−0.196	0.173
Hired labor	−0.183	0.289
Family-hired labor	−0.134	0.131
Owned land	0.466	0.362
Both owned and rented land	−0.758*	0.441
Herbicides	0.066	0.308
Pesticides	−0.391	0.354
Grain price	0.001***	0.001
Extension	0.013	0.106
Age	−0.015	0.012
Gender	0.300**	0.150
Size of household	0.008	0.029
Education	0.017	0.022
Farm size	−0.110*	0.059
Sorghum demonstrations	−0.085	0.118
Off-farm income	0.249**	0.109
Experience	0.016	0.011
Productivity(CF)		
Kongwa	0.006	0.141
Chamwino	0.098	0.141
Hired labor	0.133	0.223
Family-hired labor	0.238	0.152
Owned land	0.190**	0.079
Both owned and rented land	−0.183	0.154
Herbicides	−0.105	0.297
Pesticides	−0.037	0.090
Grain price	−0.003	0.003
Extension	0.128	0.082
Age	0.010***	0.004
Gender	−0.161	0.102
Size of household	−0.039**	0.018
Education	0.028**	0.011
Farm size	0.003	0.016
Sorghum demonstrations	−0.006	0.086
Off-farm income	0.088	0.104
Experience	−0.010	0.007
CF participation		
Kongwa	0.218	0.264
Chamwino	0.573*	0.338
Hired labor	0.931*	0.509
Family-hired labor	0.723***	0.217
Age	0.030***	0.010
Gender	−0.285*	0.159
Size of household	−0.120***	0.041
Farm size	0.131*	0.075
Off-farm income	0.453***	0.163
Financial access	0.729***	0.226
Experience	−0.060***	0.012
Groups per village	−0.093**	0.047
lnS0	−0.188	0.662
lnS1	−0.655	0.136
r0	−0.109	0.161
r1	1.305***	0.497

significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.
Source: Field data

emphasizes that good market conditions facilitate the adoption of technologies at the farm level for NCFs in regions where sorghum production is mostly subsistence farming and market access is limited. There is also a positive relationship between age and productivity among CFs. Older farmers may obtain better crop performance and income as they often favor contracts that provide significant input support [34]. This implies that older farmers' experience and established networks are necessary for navigating contracts and resource allocation. However, the productivity gender gap among NCFs suggests that women face limited resources that require gender-based interventions to enhance productivity, as argued in Ref. [35]. Improvements in market access, resource use, and technology adoption by the brewing companies and other stakeholders have become essential in Tanzania, with more inclusive support provided to women and younger farmers. Addressing gender disparities in agriculture is fundamental to unlocking the full

Table 4
The effect of CF on sorghum productivity: ESR estimates

	Outcome				
Productivity (kg/ha)	CFs	NCFs		t-value	change (%)
ATT	7.00(0.01)	6.25(0.03)	0.75***	23.06	12.00
ATU	7.55(0.09)	5.91(0.04)	1.64***	15.63	27.75

CFs = contract farmers; NCFs = non-contract farmers.
t-values indicate the statistical significance of ATT estimates with significance levels: $p < 0.001$.
Values in parentheses represent standard errors.
Source: Field data

Table 5
The effect of CF on sorghum productivity: PSM estimates.

	Matching methods		
Productivity (kg/ha)	Nearest neighbor	Radius	Kernel
ATT	0.714 (0.225)***	0.760 (0.051)***	0.817 (0.174)***
change (%)	10.19	10.85	11.60

t-values indicate the statistical significance of ATT estimates with significance levels: $p < 0.001$.
Values in parentheses represent standard errors.
Source: Field data

growth potential of rural farming communities.

Productivity among CFs is likely negatively affected by larger household sizes. Higher dependency ratios and limited financial resources may hinder farmers' access to additional inputs beyond those the contract provides. According to Ref. [36], most farmers with larger families in rural areas prefer food security over commercial production, limiting productivity under CF. Thus, the pressure on household resources may reduce the capacity of sorghum farmers, especially CFs, to take full advantage of the CF benefits by adopting improved seeds or extension services in Tanzania. The inverse relationship between farm size and productivity for NCFs may imply the potential to manage small plots, as supported by Refs. [7,37]. This becomes very important to NCFs in Tanzania, where sorghum farming is largely subsistence-oriented, and NCFs must rely on intensive management of smaller plots to maintain yields. This suggests that while CF may provide necessary support of inputs and market access, its effectiveness is likely limited by household dynamics, and for NCFs, smaller and intensively managed farms may be a more viable productive strategy.

Formal education increases the productivity of CFs because farmers become more receptive to opportunities and new information, as supported by Refs. [38,39]. In the context of sorghum farmers working with TBL, educated farmers are better equipped to adopt improved seeds and use the provided technical support, resulting in higher yields and better market access. Further, off-farm activities enhance NCFs ability to invest in improved technologies that enhance yields, as argued by Ref. [40]. This highlights the role of diversification in enhancing livelihoods in rural areas, where farmers' vulnerability to agricultural risks is reduced, and productivity is further enhanced, mainly where formal market options are limited.

4.2. Determinants of CF participation among sorghum farmers

This study also sheds light on the contextual factors influencing CF participation in Tanzania and offers insights for sorghum farmers and other stakeholders. Younger farmers are less receptive to joining CF, likely finding alternative income sources more attractive [41,42]. This means that older farmers consider CF a means to get better technologies and access stable markets while improving productivity. In this case, CF has advantages such as improved seeds and assured markets that are more attractive to older farmers. Younger farmers might be more receptive to innovations and initiatives but need more resources. Such resource constraints could result in low motivation on their part to join CF. This highlights the need for CF policies that target both age groups in CF through targeted incentives and engagement strategies such as access to loans and technology, addressing the challenges of smallholder farmers, and promoting inclusive agricultural growth. For Chamwino district, stronger social networks lead to increased CF participation, indicating that areas with weaker networks may not access essential information, resulting in low participation. In addition, strategies to build local networks, such as promoting outreach programs to ensure all smallholder farmers can benefit from CF regardless of their social networks, might make the brewing company's efforts at involving sorghum farmers more effective.

Farmers involved in off-farm activities and those who used hired or mixed labor may join CF, likely due to access to resources for investing in commercial production [43] but also due to the rising commercial value of sorghum in the study area. This suggests that diversification into non-farm activities can complement farmers' participation in CF by providing additional income, enabling farmers to invest in agricultural inputs essential for successful CF involvement. Such supplementary income enhances their resilience to agricultural risks, making them more likely to adopt CF as they seek to maximize profits. Hence, policies encouraging diversification can promote CF and farmers' economic viability. Further, farmers with larger farm sizes and better credit access are highly engaged in CF because of their inherent investment capacity and economies of scale. Larger farms give farmers a good chance to produce in higher quantities to meet the contract's requirements, and access to credit increases their capacity to invest in crucial resources such as quality seeds and fertilizers. Meemken and Bellemare [44] acknowledge credit as one of the important factors for CF. The support for access to credit and the ability to help farmers expand their farm sizes enhance CF participation and agricultural productivity among smallholder farmers.

Women's participation in CF reflects limited resources and a shift toward promoting gender equity, driven by government policies and private sector initiatives [45]. This shift aims to empower women by providing them with better access to resources and training, enabling them to contribute effectively to agricultural production. However, large families may face barriers to joining CF due to their dependence on subsistence agriculture [2]. The demands of supporting larger households can constrain the ability to participate in CF. Experienced farmers and those in villages with several farmer groups are also likely to be indifferent to CF as they are knowledgeable about agriculture practices and, therefore, can easily access such information. Thus, farmers are less inclined to join CF if they feel their current practices are secure or if CF risks are more significant than the perceived benefit. Farmer groups can create an enabling environment where knowledge and resources are shared among members, reducing the perceived need for formal contracts.

4.3. The effect of CF on sorghum productivity

While the ESR effectively addresses unobservable factors, we used PSM as a complementary method to validate the results. Using these two approaches strengthens the credibility of the findings. The consistency of the two models' results suggests that confounding factors do not drive the observed productivity benefits but can be attributed to CF.

The anticipated productivity benefits of CF can be attributed to its facilitative role in providing access to essential resources and technical assistance [19,46,47]. In Tanzania, the brewing company's CF initiative has been shown to enhance productivity through access to better seeds, technical support, and financial services. However, some limitations persist, for instance, the brewing company does not supply additional inputs like fertilizer, pesticides, and herbicides, which are essential for maximizing productivity. Consequently, this lack of additional inputs limits farmers' ability to benefit from CF fully. Therefore, efforts from stakeholders are needed so that CF can fully benefit smallholder farmers. Different studies highlight the impacts of CF on productivity across contexts. For example, it is recorded that there was a 27 % increase in the productivity of rice in Ghana [7], while cashew and tobacco CFs in Ghana and Zimbabwe obtained productivity gains of 37 % and 39 %, respectively [18,21]. Thus, CF appears to be a viable strategy for fostering transformation and promoting economic growth among smallholder farmers in SSA. Importantly, CF equips farmers with the necessary means and stability to navigate global challenges, such as climate change, market volatility, and food insecurity. This highlights the need to strengthen CF programs through support policies, ensuring that farmers have the resources to enhance productivity.

Although past studies have highlighted the impact of CF on farm productivity, research focusing on food crops such as sorghum, maize, and rice in East Africa remains limited [9]. Therefore, this study contributes significantly to literature, particularly its impact on sorghum productivity. Furthermore, most studies in East Africa, for example, [10,11], have only provided descriptive analyses of CF's benefits to productivity, without employing robust methods to address selection bias and endogeneity. By employing more rigorous methods, this study addresses these gaps and demonstrates how CF can be viable for improving smallholder farmers' livelihoods. Moreover, researching CF for food crops is also essential for enhancing economic resilience among farmers growing these crops. This calls for future studies to explore CF under different contexts, particularly food crops, to inform policies promoting productivity and sustainability.

4.4. Study limitations and future research

We acknowledge several limitations in this study. Although ESR and PSM methods address selection bias and endogeneity, cross-sectional data are limited in establishing a clear causal relationship between CF and productivity, as cross-sectional data do not account for year-to-year changes or long-term trends affecting CF participation and resulting outcomes. While these findings are informative, they cannot capture the dynamics of agricultural practices over time. Moreover, based on observational data, the impact assessment approach is non-experimental; thus, endogeneity could affect the results' reliability. While the study provides insight into farmers in districts such as Kongwa, Chamwino, and Mpwapwa, the findings may not be directly applicable to all regions or other value chains. However, they remain relevant for areas with similar characteristics, particularly semi-arid regions of Tanzania. Therefore, this calls for further studies using longitudinal data or experimental approaches to address these concerns. Further, future studies are encouraged to move beyond productivity to other outcomes such as income, profitability, and food security.

5. Conclusion and recommendations

5.1. Conclusion

The study mainly aimed to estimate the causal effect of CF on sorghum productivity rather than what drives CF participation itself, resulting in distinct analytical insights and implications. The ESR and PSM were employed to address selection bias in farmers' decisions regarding CF. Specifically, participation in CF is associated with a 12 % increase in productivity. In addition, participation in CF could increase the productivity of NCFs by 28 %. The factors determining productivity differ: for NCFs, these include owned and rented land, grain price, gender, farm size, and off-farm income, while for CFs, owned land, age, household size, and years of schooling influenced productivity. In addition, variables of CF participation include age, off-farm income, location, hired labor, farm size, financial services, household size, gender, production experience, and the number of farmer groups per village. In conclusion, this study demonstrates that CF can increase the productivity of participating farmers and can significantly enhance the productivity of non-participants. Addressing the identified determinants can facilitate higher CF participation and boost sorghum productivity in Tanzania.

5.2. Recommendations

The following recommendations from this study that can be pursued to enhance the productivity of sorghum in Tanzania, including promoting land accessibility through land tenure programs. Policymakers should introduce land registration schemes at an affordable cost and provide financial incentives to farmers for formalizing land ownership. In addition, formal education for farmers should be expanded through agricultural curricula and community learning centers to further promote agricultural development. There is a need for greater agricultural training programs on modern farming techniques and CF benefits. Policy makers should also guarantee equitable and stable grain prices through market stabilization and price information systems to support farmers. Additionally, stakeholders should promote gender-sensitive programs that enhance women's access to resources, while farmers should adopt inclusive practices to ensure gender equity in farm decision-making. Regarding off-farm activities, policymakers must encourage income diversification through training and credit for rural non-farm enterprises. Farmers should also optimize their time between farming and off-farm activities to increase productivity.

Furthermore, it is vital to strengthen policies that create incentives for CF, primarily by facilitating access to increased financial services through government-backed microfinance programs and guarantees that enable farmers to participate in CF. Moreover, non-farm growth and agro-processing development have their role in enhancing rural livelihoods and opening more sources of income beyond economic diversification supported by private financial institutions. Additionally, policymakers should enhance gender equity by providing women with equal access to CF in land, finance, and training programs. This will help minimize economic gaps between genders. These efforts will require effective collaboration between the public and private sectors to add value along the sorghum value chain. Partnerships could provide better access to resources and markets, along with stable contracts and support services for farmers. Furthermore, specific contexts in targeted areas should be considered when designing CF programs. This study also recommends that future research explore beyond the impact of CF on productivity.

CRediT authorship contribution statement

Thedy Kimbi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefan Sieber:** Writing – review & editing, Validation, Supervision, Conceptualization. **Essegbemon Akpo:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Christopher Magomba:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Fulgence Mishili:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declarations

Availability of data

The data used for this study is available upon request.

For ethics approval

This study was reviewed and deemed exempt from ethics approval by The TARI Ethical Review Committee under the Department of Technology Transfer and Partnership, with the reference number TARI/NAL/TG/T.VOL 1X/189 dated 1/10/2020.

For consent

All participants provided verbal consent to participate in the study and for their data to be published. As most farmers were illiterate, the consent form was embedded in the questionnaire and explained in the local language, and verbal consent to participation and publication was obtained before the interviews proceeded.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2025.e44260.

Appendices.

Appendix 1
Variables used in the ESR model

Variable ($\boldsymbol{X}_i$)	Unit	Description	Expected symbols		Variables justification	
			CF participation (1/0)	Productivity (kg/ha)	CF participation	Productivity
Location	Categorical	1 = farmer in Mpwapwa district; 2 = farmer in Chamwino district; and 3 = farmer in Kongwa district	+/−	+/−	[12,18]	[18]
Labor use	Categorical	1 = farmer use of own labour; 2 = farmer use of hired labour; and 3 = farmer use of family and hired labour mix	+/−	+/−	[48]	[7,49]
Type of land	Categorical	1 = using leased land; 2 = using own land; 3 = using both leased and owned land		+		[49]
Herbicides	Dummy	1 = herbicide user; 0 = none		+		[50]
Pesticides	Dummy	1 = pesticide user; 0 = none		+		[50]
Grain price	Continuous	Sorghum grain price in Tshs per kgs		+		[49]
Extension	Dummy	1 = extension services obtained and 0 = no extension services obtained		+		[50]
Age	Continuous	Farmer's age in years	+/−	+/−	[7]	[7,18]
Gender	Dummy	1 = male farmer and 0 = female farmer	+	+	[18]	[49]
Size of household	Continuous	Number of members in a household	+/−	+/−	[7,15]	[7,18]
School years	Continuous	Years spent in school obtaining formal education by a farmer		+	[7;15]	[18,49]
Farm size	Continuous	Hectares used in sorghum production	+	+/−	[51,52]	[7,18]
Sorghum demonstrations	Dummy	1 = farmer participated in on-farm demonstrations and 0 = no participation		+		[53]
Off-farm income	Dummy	1 = a farmer has an off-farm source of income, and 0 = a farmer has no off-farm source of income	+	+	[52]	[49]
Financial services	Dummy	1 = obtained financial services; 0 = no financial services	+	+	[18]	[18,49]
Farming experience	Continuous	Sorghum production experience in years	+	+	[15]	[7]
Groups per village	Continuous	Number of farmer groups per village	+/−		[14]	

Appendix 2
Abbreviations list

Abbreviation	Longform
ATT	Average Treatment Effect of the Treated Group
ATU	Average Treatment Effect of the Untreated Group
CF	Contract Farming
CFs	Contract Farmers
ESR	Endogenous Switching Regression
FIML	Full Information Maximum Likelihood
GDP	Gross Domestic Product
GoT	Government of Tanzania
IMR	Inverse Mills Ratio
KBM	Kernel-Based Matching
NCFs	Non-Contract Farmers

(*continued on next page*)

Appendix 2 (*continued*)

Abbreviation	Longform
NNM	Nearest Neighbor Matching
PSM	Propensity Score Matching
RM	Radius Matching
RUT	Random Utility Theory
SBL	Serengeti Breweries Limited
Stata	Statistics and Data
TARI	Tanzania Agricultural Research Institute
TBL	Tanzania Breweries Limited

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