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Participation in village savings and lending associations and rice profitability in Tanzania: Application of propensity score matching and endogenous switching regression

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ABSTRACT

We assess the contribution of participation in bundled service-bundled VSLAs on rice productivity and profit among smallholder rice farmers in Mvomero District, Tanzania. The study propensity score matching (PSM) and endogenous switching regression (ESR) models, and found that participation in VSLA has a positive and significant contribution to rice productivity and profit for smallholder rice farmers. Participation in VSLAs increases farmers' ability to regenerate income for investing in improving productivity and profitability and enhancing rice sector development. VSLAs prove as a tool for building financial capital through savings and easy access to credit in rural areas. This study improves on existing research and offers new insights into the effects of VSLA as one of the financial inclusion tools on the economic activities of agricultural households in Tanzania.

1. Introduction

In many countries in Africa, the larger portion of the diet constitutes rice, and currently, the demand for rice is growing and is expected to increase to 2.27 million tons in the next 5 years from 2.05 million tons in 2018 [1]. In Tanzania, rice has been selected to be among the country's strategic commodities due to its contribution to food security and the economy of households and the country as a whole. Rice contributes about 2.7% of the national GDP and it is consumed by 60% of the Tanzanian population. Also, 90% of the rice is produced by smallholder farmers who face numerous challenges, including easy access to credit, which can be invested in farming activities and improved production.

Rice farming is the major economic activity of smallholder rice farmers in Tanzania. However, farmers face difficulty in accessing credit from formal financial institutions due to a lack of collateral and other requirements of formal sources [2]. In most cases, smallholder farmers own less than 2 hectares of land and the majority of the land owned cannot be pledged as collateral required by the formal financial institutions ([2] and [3]). Despite the potential of the crop, difficulties in accessing credits from formal financial institutions have led to low rice productivity [4]. Agricultural credit is recognized to play a vital role in agriculture, in particular, and overall economic development as it facilitates timely access to agricultural inputs [5,6]. The study by Martey et al. [7] reported that credit is important to smallholder farmers as it enhances the timely access and use of appropriate agricultural inputs.

Agricultural credit is one of the important components to be strengthened to enhance improvement in agriculture productivity in Tanzania [8]. It can be used as capital for purchasing recommended farm inputs and improved technologies, which are the main factors for agriculture production [9]. Among the initiatives taken by the government to facilitate access to credit was the establishment of Agriculture Development Banks (ADB) and the emergence of numerous microfinance institutions (more than 500 in 2013) to help low-income people with fair credit. But to a greater extent, it has not yet solved the problem of access to credit for smallholder farmers due to a lack of awareness, bureaucratic application, processing procedures, collateral requirements, and centralization [10].

In response to the challenge, HELVETAS Tanzania, during the implementation of Rice Postharvest Management and Marketing (RIPOMA), introduced the Village Savings and Lending Association (VSLA) which bundled with services to facilitate easy access to credit among smallholder rice farmers of the Mvomero District. The VSLAs involve groups of 20–30 members, who mobilize savings and take small credits from them at affordable and agreed-upon interest rates [11]. However, the RIPOMA VSLAs also provide collective services that are collective input purchase, collective marketing and collective

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warehouse services. The studies by Grossman [12], Boukhali [13] and Ngegba *et al.* [14] revealed that VSLAs improved the lives of farmers in rural areas. According to Theophilus and Paul [15], women who participate in credit and savings associations are more active socially and economically than those who do not participate.

The basic question leading this study is whether participation in VSLAs bundled with services had a great contribution to rice productivity and profitability among smallholder rice farmers in the Mvomero District. Assuming that farmers who participate in VSLAs can have access to credit which can be invested in rice farming to purchase necessary inputs and increase productivity and profitability. Therefore, this study has attempted to assess the contribution of participation in VSLAs bundled with other services than credit and savings on rice productivity and profitability among smallholder rice farmers, using propensity score matching and endogenous switching regression methods to ensure robustness for reducing or eliminating biases in observational studies.

2. Research methodology

2.1. Description of the study area

The study was conducted in the Mvomero District, Morogoro (Fig. 1). The Mvomero District is located at latitude 06° 26′ south and longitude 37° 32′ East. The district occupies a total area of 7325 square kilometers whereby 549,375 hectares are suitable for crop cultivation. According to the Tanzanian National Census [16], the district's population was 312, 109, of which 154,843 were males and 157,266 were females, with an average household size of 4.3 people. The average rainfall per year ranges from 600 mm to 2000 mm.

The Mvomero District was chosen as a study area based on the fact that the district was one of the areas where the RIPOMA project was implemented and the VSLA groups established were 67 compared to 31 groups in the Kilosa District. Therefore, it was easy to get enough respondents for the study.

2.2. Research design

The study adopted a cross-sectional research design which allows the collection of similar data from different groups of respondents at a single point in time [17]. Cross-sectional research is considered to be favorable in this particular study since it is economic and allows comparison of the variables of interest from the stallholder rice farmers at the same time without additional cost. However, in cross-section studies, it is difficult to make causal inferences, and it cannot be used to study behavior over a period it is used in many studies to compare many different variables and groups at the same time [18].

2.3. Sample size and sampling procedure

A multi-stage sampling was used to draw the appropriate sample from the study population. In the first stage, the Mvomero District was selected purposively due to its participation in the implementation of the RIPOMA project. In the second stage, the three wards were selected randomly from the eight RIPOMA project wards. In the third stage, 18 groups, which were beneficiaries of VSLAs, including Utulivu, Uwezo, Twitange, Jembe Mkombozi, Chawahe, Uyanjo, Kilimo Kwanza, Busara, Endelevu, Uhuru, Mtego wa Simba, Maendeleo, Tushikamane, Ushauri, Mandela, Divue, Wapendanao and Hiari were selected purposively.

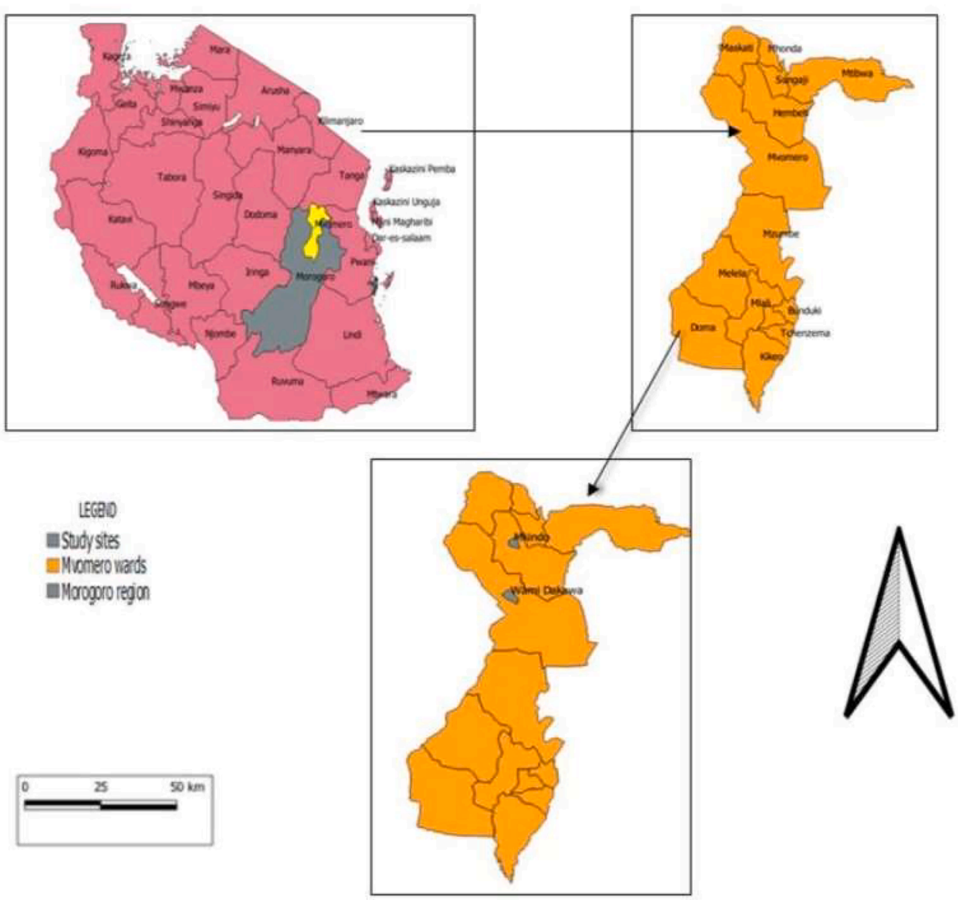

Fig. 1. Map of the study area (Mvomero District) of Morogoro Tanzania.
Source: researchgate.net

Thereafter, 145 respondents (VSLA participants were selected randomly from 18 VSLA groups. On the other hand, 205 non-VSLA participants were selected randomly from the same wards which constituted the sample size for the study, which was determined by Yamane [19] method of sample size determination as presented in Eq. (1).

Sample formula

$$n = \frac{\mathrm{N}}{1 + N^*(e)^2} \tag{1}$$

n represents the sample size

N represents population size

e represents margin of error (allowable error (%)/ level of precision/ degree of accuracy).

The population with the particular characteristics is 6541 which is the approximate total number of rice farmers in Mvomero disrict with the degree of accuracy is 8%.

$$n = \frac{6541}{1 + 6541^*(0.002704)}$$

$$n = 350$$

Therefore, the sample size is 350 rice farmers.

The sample size used in this study was of 350 respondents as calculated above. Also, this sample size was justified by the sample sizes used by other studies conducted using propensity score matching and arrived with the intended results. The samples used by the other studies ranged from 342-473 households [5,20–22]. The distribution of the sample used in this study is as indicated in Table 1.1.

2.4. Data collection

The quantitative data for this study was collected through a household survey, which was based on questionnaires administered to the sampled rice smallholder farmer households. Before data collection, the authority at the district level was informed and the exercise was approved. Quality assurance was engrained in all key study milestones, including recruitment of research assistants, data collection, and analysis.

2.5. Data processing and analysis

Qualitative data was sorted, coded, summarized, and analyzed using STATA 17, whereby descriptive and inferential statistics were used to analyze quantitative data. The contribution of participation in the VSLAs on rice productivity and farm profitability was analyzed using propensity score matching (PSM). The PSM approach has been used to attain balance or comparability of treatment and control groups in terms of their socioeconomic characteristics thereby controlling for confounding bias in estimating treatment effects [21]. The instrumental variable (IV) was intended to be used to check the robustness of the PSM if the Wu-Hausman F test confirms the presence of endogeneity.

Table 1.1
Participant per study ward.

Study wards	VSLA Participants	VSLA non-Participants	Pooled
Hembeti	40	70	110
Mkindo	40	70	110
Sungaji	65	65	130
Total	145	205	350

2.6. Analytical framework

2.6.1. Testing of endogeneity

The participation in VSLAs was non-randomly selected, instead determined by socioeconomic characteristics, which may influence participation and may also affect rice productivity directly. Therefore, the decision on whether to participate or not to participate was unobservable, which may have resulted in a correlation between the error term/residual and the independent variable. To assure robustness of methods used in the assessment of the contribution of VSLA participation on rice productivity and profitability, the endogeneity was tested using Wu-Hausman test Table 1.2, and the variables used were age, sex, marital status, education level, farmer experience, household size, head of household main occupation, family labor, land ownership, land size, harvesting method, and VSLA participation.

The results in Table 1.2 show that P-Value is greater than 0.05 means the null hypothesis cannot be rejected. Therefore, the models are not systematically different. Thus, to ensure robustness of PSM, endogenous switching regression were used to assess the contribution of VSLA participation on rice productivity and profitability of rice farmers in Mvomero District.

2.6.2. Propensity score matching

Given the lack of baseline data and the voluntary nature of the participation, propensity score matching was used to assess the contribution of VSLA participation on rice profitability and checking robustness of ESR for correcting potential selection biases in observational studies that may result in biased estimates [23,24]. The households which did not participate in VSLA are termed as the “control group” and those who participate in VSLA as the "treatment group". The comparison of these groups was done by using similar socioeconomic characteristics to estimate the proper counterfactuals which fit for PSM [9].

In the first step of implementing PSM, the propensity scores were estimated by running a logistic model using the observed socioeconomic characteristics of the two groups, namely VSLA participants and non-VSLA participants. The aim was to estimate the propensity scores which affect the VSLA participation and are the conditional probabilities for an individual to participate in the program or not.

$$p(X) = p(Z = 1|X) \tag{2}$$

Where $p(X)$ is the propensity score, Z is the farmers’ decision to participate in the VSLA ($Z = 1$ if farmer participates and $Z = 0$ if otherwise), and X = Covariates (farmers’ socioeconomic characteristics). Propensity scores will be estimated by a binary logit model as presented in Eq. (2) below:

$$\begin{aligned}\mathrm{P(x)} = Z \\ &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \ldots \beta_n X_n \\ &\quad + \varepsilon_i\end{aligned} \tag{3}$$

Where by P(x) = Propensity score, X_1-X_n= Observed covariates, β_0=Constant coefficient

β_1- β_n = Coefficients (each independent variable’s weight) and ε_i is error term. The covariates used in the model were age sex, education level, marital status, land size, land ownership, household size, family labor, head of the household occupation, experience in rice farming, and harvesting method as shown in Table 1.3. The aforementioned

Table 1.2
Tests of endogeneity of VSLA Participation.

H0: Regressor is exogenous		
Wu-Hausman F test	0.50865 F (1338)	P-value = 0.47621
Durbin-Wu-Hausman chi-sq test:	0.52592 Chi-sq (1)	P-value = 0.46833

Table 1.3
Description of variables in the treatment effect model of rice productivity and profitability.

Variables	Level of measurement	Type of variable	Description	Expected sign	Measurement
Treatment variable: VSLA participation ($Z = 1$ for VSLA participation and $Z = 0$ for non-participation)					
Outcome variable					
Rice productivity(yield/area)	Ratio	Continuous	The average quantity of rice produced per area		Kg/acre
Covariates					
Age	Interval	Continuous variable	Number of years of individual farmer since born	+/-	Number of years
Sex	Nominal	Dummy	Sex of individual farmer	+/-	$D = 1$ Male, $D = 0$ Female
Marital status	Ordinal	Categorical	Marital status of the rice farmer	+/-	$D = 1$ Married, 0= otherwise
Household size	Interval	Continuous	Number of members in the household	+	Number of members
Education level	Ordinal	Categorical	The time the individual farmer spent in formal education	+	Number of years
Respondent main occupation	0rdinal	Categorical	The main occupation of respondents	+/-	1 agriculture,2 business, 3 employed
Farmer experience	Ordinal	Continuous	Number of years a farmer spent in rice farming	+	Number of years
Family labor	Interval	continuous	Number of household members who can participate in farming al labor	+	Number of members in the household.
Farm size	Ratio	Continuous	Size of land allocated for rice production	+	Number of Acres
Land ownership	Ordinal	Categorical	Land ownership status of a smallholder rice farmer	+/-	$D = 1$ owned, $D =$ 0 otherwise
VSLAs Participation	Nominal	Categorical	Whether the farmer is a member of VSLA or not	+/-	1=VSLA participant 0= non-participant

covariates were selected because they are related to smallholder rice farmers' self-selection into the VSLA intervention. Therefore, they were used as predictors for participation in VSLA in the creation of propensity scores using the logistic regression model. Some other covariates, i.e. access to credit, access to extension services, use of fertilizers, and use of improved seeds, were not included in the model because they are affected by the participation in the VSLA, and they didn't match between the two groups.

The second step was to check the socio- economic characteristic balance between the two groups, VSLA participants and non-participants. This involves checking if the two groups have similar observable socioeconomic characteristics based on propensity scores. This was done to ensure the two groups are comparable, to avoid comparing the incomparable groups [20,24], and the check was done using a histogram and *t*-test. Moreover, the balanced treatment groups attained the same traits as the randomized control trial (RCT) given the quality of the observable data [25]. The next step was matching the two groups by similar propensity scores. To ensure the quality of matches between the treatment and control groups, Nearest Neighbor Matching (NNM), caliper or radius matching, and kernel matching (KM) were used in this study [26]. The NNM relies on the nearest propensity scores between participants and non-participants, while KM focuses on comparing the outcome of each treated individual to the average weighted propensity scores of untreated individuals who have nearer propensity scores [27]. The fourth step was the estimation of the average treatment effect on treated (ATT) to assess the Contribution of participation in VSLA on rice productivity and profitability. The final step was sensitivity analysis to examine the presence of hidden biases from the unobserved covariates. The unobserved confounder may influence the results and lead to incorrect estimates [28].

2.6.2.1. Yield effect. To estimate the effect of VSLA participation on rice productivity, let P_{1i}=1 represent VSLA participants and P_{0i}=0 represents non-participants. Assume the outcomes for VSLA participants are Y_{1i} and Y_{0i} for non-participants. Then the treatment effect (Z) is presented as follows:

$$Z = Y_{1i}(P_{1i} = 1) - Y_{0i}(P_{0i} = 0) \quad (4)$$

Normally, in observational studies, there is a problem where participant Y_1 ($P_{1i} = 1$) and non-participant Y_1 ($P_{1i} = 0$) cannot be observed at the same time due to the situation of counterfactuals. Because either a participant or a nonparticipant was observed in this situation, estimating the individual treatment effect becomes difficult [9]. Therefore, ATT was used to estimate the average difference in outcomes that would be obtained by comparing the outcomes of individuals with and without treatment. ATT is presented in Eq. (4) below:

$$ATT = E(Y_{1i} - Y_{0i}|\ Z = 1) = E(Y_{1i}|Z = 1 - E(Y_{0i}|Z = 1) \quad (5)$$

Where ATT denotes the average treatment effect on the treated, it measures the correlation between VSLA participation ($Z = 1$) and rice productivity; Y_{1i} denotes the yield of a rice farmer who participates in VSLA; Y_{0i} is the yield of a rice farmer if he/she did not participate in VSLA. E (Y_{1i} | $Z = 1$ is the average yield obtained by the individuals in the presence of VSLA, whereas E (Y_{0i} | $Z = 1$ is the average yield obtained by the VSLAs participants if they were not exposed to the intervention.

2.6.2.2. Farm profit effect. In estimating the effect of VSLA on farm profit, , the gross margin (GM) analysis was applied for both VSLA participants and non-participants. The equation for GM is presented as follows:

$$GM_i = \sum_{i=1}^{n}(\mathrm{TR} - \mathrm{TVC}) = \sum \mathrm{PyY} - \sum \mathrm{PxXi} \quad (6)$$

Where TR was the total revenue from selling a bag of paddy, TVC was the total variable cost of producing a bag of paddy, and P_y and P_x are the prices of one bag of paddy and inputs, respectively, whereas Y and X_i are the quantities of paddy solid and inputs used, respectively. The average treatment effect on farm profit was given by the equation below:

$$ATT = E((P_1Y_1\ |Z = 1) - P_xX)) - ((E(P_0Y_1|Z = 1) - P_xX)) \quad (7)$$

Therefore, ATT = E (GM_i) – E (GM_0)

Where ATT denotes the average treatment effect on the treated, it measures the correlation between VSLA participation and rice farm profit. E ((P_1Y_1 | $Z = 1$)-P_xX)) is the average rice profit obtained by the individuals in the presence of VSLA, whereas - E (($P_0Y_0/Z = 1$)-P_xX)) is the average rice profit obtained by VSLA if they were not exposed to the intervention. GM1 and GM0 are gross margins for VSLAs participants and non-participants, respectively.

2.6.3. The endogenous switching regression (ESR) model

The ESR model has been identified as a model that can correct for selection bias that could arise from both observed and unobserved variables within a dataset. This model is recommended by the works such as [29–31]. In the context of this study, the contribution of Village saving and landing association is estimated in two stages. While the first stage of the effect estimation dwells on the decision by farmers to participate or not participate in VSLA as was seen in Eq. (2), the second stage estimates two outcome equations from two regimes, representing both participant and non-participant in VSLA. These two regimes are estimated as below;

$$Regime\ 1: \ Y_{1i} = \beta_1 X_i + \varepsilon_{1i} \ if \ V_i = 1 \ (VSLA \ Participant) \tag{8}$$

$$Regime\ 2: \ Y_{2i} = \beta_2 X_i + \varepsilon_{2i} \ if \ V_i = 1 \ (non-participant) \tag{9}$$

Where in;

Y_1 and Y_2 are the farmer's outcomes for regime 1 (VSLA participant) and regime 2 (non-participant) respectively.
X_i represents the vector of the covariates to be a farmer *i*,
β_1 and β_2 are parameters to be estimated ε1i and ε2i are the error terms associated with the outcome variables.

The error terms are assumed to have a tri-variate normal distribution with the following covariance having a zero mean;

$$COV(\eta, \ \varepsilon_1, \ \varepsilon_2) = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & \sigma_{\eta 1} \\ \sigma_{2\eta} & \sigma_{1\eta} & \sigma_2^2 \end{bmatrix} \tag{10}$$

Where in;

σ_η^2 is the variance of the error term in the selection Eq. (2)
σ_1^2 and σ_2^2 represent the variance of the error terms in the outcome Eqs. (8 and 9)
$\sigma_{1\eta}$ and $\sigma_{2\eta}$ are covariance of η, ε_{1i} and ε_{2i}. The covariance between ε_{1i} and ε_{2i} is not defined since Y1 and Y2 are not observed simultaneously [30]. The respective values of the error terms are non-zero since there is a correlation between the error term of Eq. (1) and the outcome Eqs. (8 and 9).

$$E[\ \varepsilon_{1i}|V=1] = \sigma_{1\eta}\frac{(\phi(Z_{i\alpha}))}{(\phi(Z_{i\alpha}))} = \sigma_{1\eta} \ \ \lambda_{1i} \tag{11}$$

$$E[\ \varepsilon_{2i}|V=0] = \sigma_{2\eta}\frac{(\phi(Z_{i\alpha}))}{(1-\phi(Z_{i\alpha}))} = \sigma_{2\eta} \ \ \lambda_{2i} \tag{12}$$

Where in,

$\phi(.)$ Represents the standard normal probability density function, (.) is the standard normal cumulative density function.

λ_{1i} and λ_{2i}represent Inverse Mills Ratios (IMR) calculated from Eq. (1) with Eqs. (11) and (12) and included in the outcome Eqs. (8) and (9) to correct selection bias from unobservable factors. This can be written as follows;

$$Y_{1i} = \beta_1 X_i + \sigma_{1\eta} \ \ \lambda_{1i} \ + \delta_{1i} \ if \ V_i = 1 \ (VSLA \ Participant) \tag{13}$$

$$Y_{2i} = \beta_2 X_i + \sigma_{2\eta} \ \ \lambda_{2i} \ + \delta_{2i} \ if \ V_i = 0 \ (Non-Participant) \tag{14}$$

Where in;

δ_{1i} and δ_{2i} are error terms with conditional zero means

To guarantee the reliability of the estimated results, this study employed an endogenous regression using the Full Information Maximum Likelihood (FIML) approach [32]. The ESR model necessitates the presence of a variable, denoted as Z, that is not part of the predictor (X) variables. This variable serves as the exclusion restriction. In the initial selection Eq. (2) mentioned earlier, two potential instruments were included among its variables. These instruments could influence farmers' participation decisions without directly affecting their crop productivity or farm profitability. The first instrument used was the variable "land ownership". Farmers were asked if they own land and their responses were coded as dummy responses with 1 for those who own them and 0 for those who didn't own land. This instrument could influence farmers participating in VSLA given that those who owning land there are more trusted to join VSLA than those who do not owning land. The second instrument used was "experience in rice farming" number of years in rice farming. Experience in rice farming influence VSLA participation decision farmers who were more experienced in rice farming they were also experienced in credit access and management.

To assess the validity of the two instruments concerning participation decisions and outcome variables, a Probit regression is employed for selection Eq. (2), while an OLS regression is used for outcome Eqs. (8) and (9). The significance of the variables is examined in these equations to identify their effect. The findings revealed a notable effect on the adoption decision by both instruments (land ownership and rice farming experience). However, there was a significant effect on participants' outcomes, whereas there was no significant correlation between non-participants' rice productivity and profitability. From the equation on the distribution of the error terms, the log-likelihood function can be expressed as follows;

$$Ln\sum_{i=1}^{n} A_i\left[\ln\phi\left(\frac{\epsilon 1i}{\sigma 1}\right) - \ln\sigma_1 + \ln\phi(\theta_{1i})\right] + (1-A_i)\left[\ln\phi\left(\frac{\epsilon 2i}{\sigma 2}\right) - \ln\sigma_2 + \ln(1-\phi(\theta_{2i}))\right]\Bigg\} \tag{15}$$

Where in

$\theta_{ji} = \frac{(zi\alpha+(\rho j \quad \epsilon ji) \quad \sigma j}{\sqrt{a^2+b^2}}$, With $j = 1{,}2$ and $\rho j \left(\rho \ \ _{1=\frac{\sigma_1^2}{\sigma_v}}\sigma_1 \ and \ \left(\rho \ \ _{2=\frac{\sigma_{2\eta}^2}{\sigma_\eta}}\sigma_2\right)\right.$ represents the correlation coefficients of the error term of the selection Eq. (1) and the error term of the outcome Eqs. (8 and 9). During the estimation, if any of the correlation coefficients of $\rho \ _1$ or $\rho \ _2$ are statistically significant, it confirms the issue of a selectivity bias resulting from un-observed variables [33], and this further justifies the appropriateness of the Endogenous switching regression model.

If $\rho \ _1 > 0$ indicating negative selection bias implies that farmers with below-average outcomes will most likely choose to participate in VSLA.

When $\rho \ _1$ or $\rho \ _2$shows alternative signs, it indicates that farmers choose to participate in VSLA based on the comparative advantage they observed in which participants have above–average outcomes from participant and non-participant have below-average from not participating in VSLA. The estimated coefficients from the ESR analysis enable the calculation of the average treatment effect on the treated (ATT). As such, the observed and un-observed participation counterfactual outcomes can be derived as follows;

$$E[Y_{1i}|V=1] = \beta_1 X_i + \sigma_{1\eta} \qquad \lambda_{1i}(Participant) \tag{16}$$

$$E[Y_{2i}|V=0] = \beta_2 X_i + \sigma_{2\eta} \qquad \lambda_{2i} \ (Non-Participant) \tag{17}$$

$$E[Y_{2i}|V=1] = \beta_2 X_i + \sigma_{2\eta} \quad \lambda_{1i} \ (Participants \ had \ decided \ not \ to \ participate) \tag{18}$$

$$E[Y_{1i}|V=0] = \beta_1 X_i + \sigma_{1\eta} \quad \lambda_{2i} \ (Non-participant \ had \ decided \ to \ participate) \tag{19}$$

The observed outcome (a), for VSLA participant, is computed from Eq. (16) while Eq. (17) computes the observed outcome (b) for VSLA non- participant. The expected outcome (c) from Eq. (17) represents the counterfactual of the observed outcome (a) earlier computed from Eq. (16). This expected outcome expresses what would have happened if the farmers had decided not to participate in VSLA. On the other hand, Eq. (19) is the counterfactual outcome (d) for the observed outcome of Eq. (17), representing the scenario under which the farmers decided to participate in VSLA. Un-bias treatment effects can be computed from these outcomes in Eqs. (16) to 19. The ATT (average treatment effect on the treated) is calculated as the difference observed between Eqs. (16) and 18 (a–c) while the average treatment effect on the untreated (ATU), represents the difference observed between Eqs. (18) and (16) (d-b), ATT and ATU are calculated as follows;

$$ATT = E[Y_{1i}|V=1] - E[Y_{2i}|V=1] = (\beta_1 - \beta_2)\ X_i + \lambda_{1i}\ \ (\sigma_{1V} - \sigma_{2V}) \tag{20}$$

$$ATU = E[Y_{1i}|V=0] - E[Y_{2i}|V=0] = (\beta_1 - \beta_2)\ X_i + \lambda_{2i}\ \ (\sigma_{1V} - \sigma_{1V}) \tag{21}$$

3. Result and discussion

3.1. Socioeconomic characteristics of smallholder rice farmers in the Mvomero district

The descriptive values of socio-economical characteristics of the smallholder rice farmers in the Mvomero District are presented in Table 1.4. The results reveal that the majority of smallholder rice farmers who participated in VSLA have an average age of 42 years compared to non-VSLA participants who were 39 years. This implies that it is likely easier to save the elderly in groups than the younger ones. This result is consistent with the one reported by Alesane *et al.* [34]. The respondent's education level implies that the majority of the respondents attended primary education for both participant and non-participant (82%) with farming as their main occupation (91%). The average household size for VSLA participants was 4.8 and 4.9 for VSLA non-participants. Moreover, the average household family labor for participants was 2.4 and 2.6 for VSLA non-participants. This implies that families with less family labor were more likely to join VSLAs than those with more family labor.

The non-VSLA participants had more experience in rice farming for an average of 12 years compared to the VSLA participants, who had an average of 10 years in rice farming. The majority of VSLA participants have access to extension services (87%) compared to non-participants (55%). In addition, 70% of the smallholder rice farmers in Mvomero have access to credit from different sources. By comparing the two groups, 95% of the VSLA participants had access to credit, while only 48% of the non-participants had access to credit. The source of credit for participants was the association's mobilized savings. In contrast, non-participants received credit from different sources, including banks, SACCOS, and individual lenders.

Table 1.4
Descriptive values of socioeconomic characteristics of smallholder farmers in Mvomero district.

Variable	VSLA participants 145 Mean/ proportional	VSLA non-participants 205 Mean/proportional	Total Sample
Age	42.283(10.52)	39.049(11.098)	40(10.964)
Sex	0.289	0.322	0.309
Marital status	0.731	0.708	0.717
Education Level	2.062	2.103	2.086
Household size	4.835(1.467)	4.878(1.7005)	4.86 (1.606)
Family Labor	2.455(1.0406)	2.649(1.07260)	2.569 (1.062)
Land size	1.061(0.5418)	1.026(0.6165)	1.04 (0.586)
Landownership	0.586(0.494)	0.531(0.500)	0.554 (0.498)
Household occupation	1.173	1.093	1.125
Experience in rice farming	10.883(6.954)	12.069(8.916)	11.577 (8.171)
Harvesting method	1.173	1.23	1.206
Access to extension services	0.87(0.330)	0.55(0.498)	1.251 (0.677)
Access to credit	1(0)	0.48(0.501)	0.7(0.458)

Note: *The standard deviations are shown in parentheses.*

3.2. Econometric results on effect of VSLA participation on rice productivity and profitability

3.2.1. Estimation of the propensity scores

The propensity scores of smallholder rice farmers' participation in VSLA were estimated by the application of a logistic model as a function of observable farmers' characteristics as shown in Table 1.5 below. The generated propensity scores of the two groups, VSLA participants and non-participants were used to create the comparison group in which the impact of VSLA participation was measured.

As specified in the model, the value of Pseudo R-square=0.074, the pseudo-R-square close to zero, which is 0.074, indicates a successful balance between the two groups has been achieved. The log-likelihood of-2,199,605 and significance level of 1% indicate the fitness of the model to the data. The age of the respondents, their main occupation, and experience in rice farming were statistically significant at 0.01, 0.01, and 0.05 levels of significance, respectively. Also, results are consistent with the previous findings by Alesane *et al.* [34] that elderly people are easier to save through groups than young people. On the other hand, if the respondent's main occupation is agriculture, the probability of participating in VSLA increases by 57% while other factors remain unchanged.

3.2.2. Estimation of average treatment effect on the treated with balancing check

The output presented in Tables 1.6 and 1.7 shows the results of a propensity score matching analysis on the correlation of participation in a Village Savings and Loan Association (VSLA) on rice productivity and profitability in Tanzania. The analysis assesses both treated (those who participated in the VSLA) and untreated (those who did not participate) units before and after matching based on their propensity scores.

The unmatched results indicate that the productivity for treated units was 22.3542, while for control (untreated) units, it was 19.5902, resulting in a difference of 2.7639. The standard error (S.E.) of this difference was 0.6100, and the t-statistic was 4.5300, indicating a statistically significant difference at the 0.05 level as shown in Fig. 1.

The unmatched results indicate that the productivity for treated units was 410,678.42, while for control (untreated) units, it was 275,172.78, resulting in a difference of 135,505.65 which is almost half of the treated profitability value. The standard error (S.E.) of this difference was 22,808.15, and the t-statistic was 5.94, indicating a statistically significant difference at the 0.05 level as shown on Fig. 1 on the variation and distribution between treated and untreated unit.

On the other hand, Fig. 2 shows that the propensity score was rigorously distributed between 0 and 0.8, and therefore, there is sufficient overlap between the propensity scores of participants and non-participants with the larger area of common support. Additionally, hand, not too many probabilities are concentrated near zero or eight. Thus, there is no evidence of the overlapping assumption of propensity score matching being violated as the two estimates have their respective masses in the region where they overlap and create common support (Fig. 3). Therefore, the overlap is acceptable and the balance is obtained among participant and non-participant groups.

After matching on the case of productivity, the Average Treatment Effect on the Treated (ATT) is calculated, revealing a post-matching productivity difference of 2.8733 with a standard error of 0.6827 and a t-statistic of 4.21. Despite the reduction in the magnitude of the difference after matching, the effect remains statistically significant as also revealed in Fig. 3. Similarly, in the case of profitability, the calculated ATT was found to be 410,678.42 for the treated group while 272,850.03 was obtained for the untreated group with a standard error of 25,884.24

Table 1.5
Logistic model for propensity score estimation.

VSLA	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Age	0.061	0.014	4.49	0	0.034	0.087	***
Sex	−0.396	0.271	−1.47	0.143	−0.927	0.134	
Marital status	0.152	0.267	0.57	0.569	−0.371	0.675	
Education level	−0.252	0.267	−0.94	0.345	−0.775	0.271	
Household size	0.031	0.084	0.37	0.71	−0.134	0.197	
Family labor	−0.227	0.132	−1.72	0.085	−0.487	0.032	*
Respondent main occupation	0.572	0.263	2.18	0.029	0.057	1.087	**
Experience in rice farming	−0.065	0.018	−3.54	0	−0.101	−0.029	***
Land size	0.268	0.209	1.28	0.2	−0.142	0.677	
Landownership	0.142	0.234	0.61	0.544	−0.317	0.601	
Harvest method	−0.489	0.295	−1.65	0.098	−1.067	0.09	*
Constant	−1.514	0.911	−1.66	0.096	−3.299	0.27	
Mean dependent var	0.414		SD dependent var			0.493	
Pseudo r-squared	0.074		Number of obs			350	
Chi-square	34.945		Prob > chi2			0.000	
Log-likelihood	−2,199,605						

*** $p<0.01$,.
** $p<0.05$,.
* $p<0.1$.

Table 1.6
Balance for treated and controls check in propensity score matching of VSLA on rice productivity.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Rice Productivity	Unmatched	22.3542	19.5902	2.7639	0.6100	4.53
	ATT	22.3542	19.4808	2.8733	0.6827	4.21

Table 1.7
Balance for treated and controls check in propensity score matching of VSLA on rice profitability.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Rice Profitability	Unmatched	410,678.42	275,172.78	135,505.65	22,808.15	5.94
	ATT	410,678.42	272,850.03	137,828.39	25,884.24	5.32

and T-statistics of 5.32 which is statistically significant at 0.05 level of significance.

Table 1.8 presents the distribution of treatment and control units before and after the Average Treatment Effect on the Treated (ATT) adjustment through propensity score matching in the context of the VSLA (Village Savings and Loan Association) study with a total sample size of 349. Prior to adjustment, there were 205 untreated units and 144 treated units, indicating an imbalance in the distribution. However, after implementing the ATT adjustment, the distribution of treated and untreated units became more balanced, with 205 units in each group. Results in Table 1.8 suggest that the matching process successfully achieves balance in the distribution of treated and untreated units on support, enhancing the validity of subsequent analyses by minimizing potential confounding factors and allowing for a more accurate assessment of the correlation of VSLA participation with the studied outcome.

Results obtained in Tables 1.6 and 1.7 revealed that participating in a VSLA is associated with a statistically significant increase in rice productivity and profitability. Before matching, treated units exhibited higher productivity and profitability compared to control units, and this difference persisted even after propensity score matching. The ATT represents the estimated average effect of participating in the VSLA on the treated group, indicating that, on average, those who participated had a profitability and productivity level that was 137,828.39 and 2.8733 respectively units higher than if they had not participated, the broaden results on balancing based on treatments characteristics is shown on Fig. 4 whereby most of the matched characteristics seems to be situated near zero hence reduce the possibility of huge biases of characteristics.

The socioeconomic characteristic between VSLAs participants and non- participants where balanced using a two-sample *t*-test and the distribution of estimated propensity scores (histogram). The two-sample *t*-test results in Table 1.9 indicate that 93% of socioeconomic characteristics between VSLAs participants and non-participants are insignificance at the p-value of 0.05. The results imply that there is no statistical difference in sex, education level, household size, marital status, land size, land ownership, family labor, head of the household occupation, experience in rice farming, and harvesting method. Therefore, the two groups were homogeneous and comparable.

3.2.3. *Average effect of participation in the VSLAs on rice productivity and profitability*

After balancing the socio- economic characteristic of the two groups and achieving the common support, the correlation of VSLA participation with rice productivity and farm profit was estimated. The correlation of VSLA participation was estimated using matching methods that compare the individual household outcomes of participants and non-participants using propensity scores. Given the observable characteristics matching estimates are balanced between the two groups, the estimators could vary depending on how the match's controls are defined and assigned weight.

From the estimations in Table 1.10 above, the ATT value of 1.997 for treated implies that rice productivity for VSLA participant households is higher by 1.997 bags of rice =199.7 kg/season than that of the non-VSLA participants. On the other hand, the ATT value of TZS 108,019 for rice profit implies that the rice profit of VSLA participant households is higher by TZS 1087,019 than that of the non-VSLA participant households.

However, correlation estimations with radius and kernel matching suggest that the participation in VSLA has a significant positive effect on rice productivity and profitability. The rice productivity and

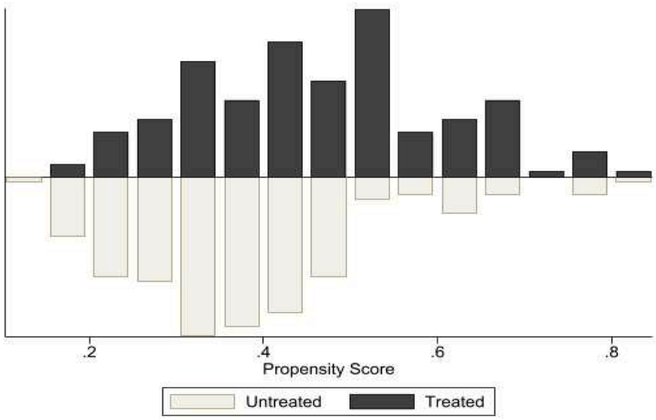

Fig. 2. Propensity score graph showing variation of treated and untreated.

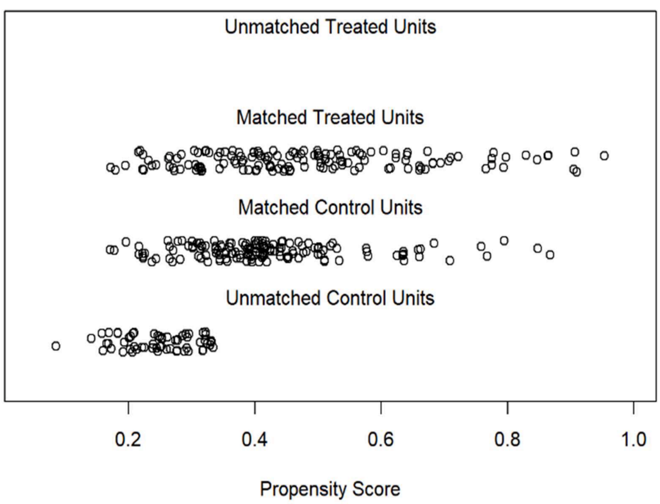

Fig. 3. Distribution of propensity score across treatments units .

profitability for VSLA participants are higher by 2.431 bags and TZS 118,000 respectively for radius matching and 2.776 bags and TZS 142,255 for kernel matching.

Generally, after matching the two groups, the results indicate that participation in VSLA had a positive and significant contribution on the rice productivity and profitability of smallholder rice farmers, as indicated in Table 1.10. The VSLA participants obtained an average of 2.401 bags/acre/season of rice, higher than their counterparts, and this implies that VSLA participants were better off in rice farming than non-participants. The p-value for both methods is below 0.05 and this indicates that the null hypothesis was rejected in all correlation estimation methods at 0.1%, 1%, and 5% significance levels respectively. On the other hand, the results indicate that VSLA participants can access credit or shares from the groups and purchase inputs and manage farm operations on time, which led to an increase in production per area which had an effect on rice profit and wellbeing more than non-participants. Moreover, the study findings show that VSLA non-participants had no reliable source of credit and that few of them (48%) had access to credits from individual landers at high cost and not at the proper time. Also, VSLA participants had an opportunity to collectively purchase inputs where they formed an umbrella known as the input market association (IMA), which operates at ward level. The umbrella purchases inputs collectively and distributes them to VSLA groups. Furthermore, the inputs are distributed to VSLA members at a lower cost and time before the season. The credit accessed from VSLA enables VSLA participants to afford short-term rice farming technologies which have a positive effect on rice productivity and profitability.

Table 1.8
Treatment and common support after ATT adjustment in PSM VSLA ($n = 349$).

Treatment	On support	Total
Untreated	205	205
Treated	144	144

These findings are also supported by results from previous studies such as Dawuni et al. [9] which reported that VSLA participation has a positive and significant effect on farm value chain productivity where VSLA participants had more units due to timely purchase and use of inputs and technologies. The studies by Karlan *et al.* [35] and Kizza [36] found that VSLA participation has positive results for businesses, especially for women, who are the primary target of the associations. Also, the study by Ngegba et al. [14] reported that VSLA has improved farm profit and enables the farmers to manage medical services and school fees for their household members. Moreover, the study by Nyamaka [37] concluded that VSLA financial services methodology contributed to the improvement of livelihood for the VSLA members. The study by Dagunga *et al.* [38] on the impact study of VSLA on agricultural technology adoption concluded that promoting VSLA groups improves smallholder farmers' saving capacity for agriculture investment.

3.2.4. *Sensitivity analysis*

The Rosenbaum bounds sensitivity analysis was performed to check the presence of hidden bias caused by the unobserved covariates between participants and non-participants.

Table 1.11 shows that the p-critical values of all outcome variables estimated at various levels of critical values of gamma are significant at p-value less than the usual value of 0.05, which infers that the main covariates which affect the participation in VSLA and the outcome variables have been considered, and changes in gamma values didn't change the study inferences. Therefore, the positive effect of VSLA on rice productivity and farm profit is insensitive to potential hidden bias due to an unobserved confounder

3.2.5. *Endogenous switching regression results*

The Full Information Maximum Likelihood (FIML) estimates of the endogenous switching regression model for the VSLA participation equations are presented in Table 1.12 and Table 1.13. The estimated coefficients of the selection equations for both rice productivity and profitability are significantly different from zero. This suggests that both observed and unobserved factors influenced farmers' decisions on the

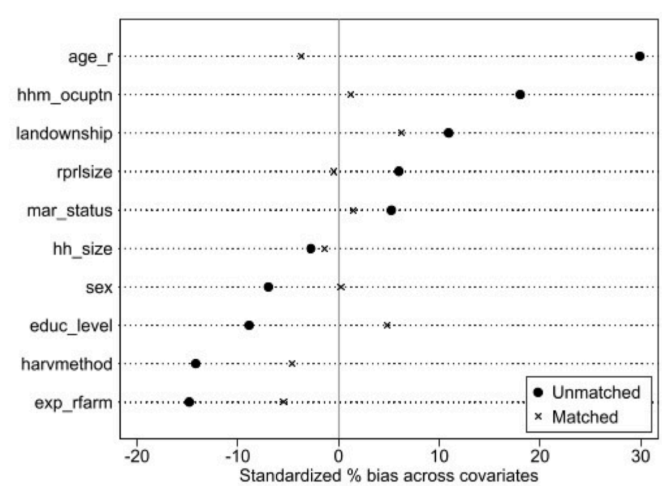

Fig. 4. Socio-economical characteristics of VSLA participants and non-participants.

Table 1.9
Balanced socio-economical characteristics of VSLA participants and non-participants.

Variable	Unmatched Matched	Mean Treated	Control	%reduction %bias	Bias	*t*-test t	*p*>*t*	V(T)/ V(C)
Land size	U	1.0642	1.0256	6.7		0.61	0.545	0.77
	M	1.0642	1.0671	−0.5	92.6	−0.04	0.968	0.66*
Land ownership	U	.58333	.53171	10.4		0.95	0.341	.
	M	.58333	.55216	6.3	39.6	0.53	0.595	.
Household Occupation	U	1.1736	1.0927	18.3		1.71	0.089	1.40*
	M	1.1736	1.1681	1.2	93.2	0.09	0.927	0.8
Harvest method	U	1.1736	1.2293	−13.9		−1.26	0.207	0.81
	M	1.1736	1.192	−4.6	67	−0.40	0.688	0.92
Farming Experience	U	10.903	12.068	−14.6		−1.31	0.190	0.61*
	M	10.903	11.339	−5.5	62.6	−0.49	0.626	0.73
Sex	U	.29167	.32195	−6.6		−0.60	0.548	.
	M	.29167	.29058	0.2	96.4	0.02	0.984	.
Age	U	42.076	39.049	28.3		2.59	0.010	0.85
	M	42.076	42.48	−3.8	86.7	−0.31	0.758	0.75
Marital status	U	.72917	.70732	4.8		0.44	0.657	.
	M	.72917	.72235	1.5	68.8	0.13	0.897	.
Education level	U	2.0625	2.1024	−8.8		−0.80	0.425	0.81
	M	2.0625	2.0405	4.8	45	0.42	0.676	0.87
Household size	U	4.8403	4.878	−2.4		−0.22	0.829	0.75
	M	4.8403	4.862	−1.4	42.5	−0.12	0.907	0.76

P-value ≤ 0.05.

Table 1.10
Estimation of the correlation of VSLA participation with rice productivity and Profitability.

Matching method	Outcome variables Rice productivity Nearest neighbor	Kernel	Radius	Average	Rice profitability Nearest neighbor	Kernel	Radius	Average
VSLA participation								
Participants	205	145	121		205	145	121	
Non-Participants	144	199	170		144	199	170	
ATT	1.997	2.776	2.431	2.401	108,019	142,225	118,000	122,748
STD error	0.874	0.701	0.702		30,892.74	25,298.8	26,739.53	
P-value	0.025**	0.001***	0.001***		0.005***	0.003***	0.004***	

Note: Bootstrap with 50 replications was used to estimate standard error for the propensity score matching.
*** $p < 0.01$,.
** $p < 0.05$, * $p < 0.1$.

Table 1.11
Rosenbaum sensitivity analysis for the average treatment effect on treated.

Rosenbaum bounds for Rice productivity ($N = 350$ matched pairs) Gamma	Sig+	Sig-	Rosenbaum bounds for Rice farm profitability ($N = 350$ matched pairs) Gamma	Sign+	Sign-
1	0	0	1	0	0
2	0	0	2	0	0
3	0	0	3	0	0
4	2.2e-16	0	4	2.2e-16	0
5	2.0e-13	0	5	2.1e-13	0
6	1.8e-11	0	6	1.8e-11	0
7	4.4e-10	0	7	4.4e-10	0
8	4.9e-09	0	8	5.0e-09	0
9	3.2e-08	0	9	3.2e-08	0
10	1.5e-07	0	10	1.5e-07	0

* Gamma-log odds of differential assignment due to unobserved factors; Sig+ - upper bound significance level; Sig- - lower bound significance level.

VSLA participation. This comforts our choice of model since it handles the problem of endogeneity. The results of the endogenous switching regression with rice productivity as an outcome variable considering the adoption tendency are presented in Table 1.12. The first column represents results from the first stage of the selection equation earlier defined while column represents the results of the second stage estimation for VSLA participant and column represents results for the non-Participant- rice productivity was the dependent variable and was measured in kilograms per hectare (kg/ha). The selected data set fits the chosen model as confirmed by the Wald test and the LR test (7.95) which is statistically significant at 1% ($p < 0.000$). The chosen ESR model was appropriate for the analysis unlike an exogenous model in which applying ordinary least squares would have resulted in biased results.

The second-stage endogenous switching regression model estimates for rice productivity (output per hectare) are indicated as VSLA participants and non-participants, as presented in Table 1.12. The results of the estimation highlight that land size, occupation, farming experience, sex and education coefficients are all statistically significant in influencing rice productivity among farmers who participated in the VSLA credit lending association. The coefficients of respondent farming experience, educational level and household size are in the same vein negative and statistically important in affecting non-participant rice productivity development. The findings indicate that a unit improvement in the farming experience, the number of years spent in education, and household size would result in a 10.4% decrease in rice production, 10.3% and 169.9 respectively. The conventional nature of some experienced farmers could be attributed to a plausible explanation for the negative relationship between farming experience and rice productivity. Some farmers are so content with their traditional farming method that they find it hard to switch to new farming practices, thus reducing the efficiency of production. This result is in line with Danso-Abbeam and Baiyegunhi, [39] who have noticed a detrimental association between the knowledge of farming and technological effectiveness. The number of years spent in school is negatively signed with rice productivity could also be traced to the fact that the number of years in formal education may not necessarily increase one's productive efficiency as compared to the level of knowledge in its environment of production. The result is

Table 1.12
Endogenous switching regression on farmers rice productivity.

Variables	Selection Equation	VSLA Participants	Non-Participants
Farm size	0.183(0.126) ***	1.700(0.805) **	0.444(0.678) ***
landownership	0.1024(0.142)	−0.121(0.881)	0.239(0.807)
Main occupation	0.356(0.156) **	1.820(0.930) **	0.830(1.034)
Harvest method	−0.287(0.178)	0.296(1.171)	2.734(0.983) ***
Farm-experience	−0.042(0.011) ***	−0.0754(0.063)	−0.104(0.047) **
Sex	−0.261(0.159) *	1.074(0.942)	0.442(0.665)
Age	0.035(0.008) ***	−0120(0.816)	0.239(1.053)
Marital status	0.023(0.166)	0.296(1.440)	2.736(0.887)
Education level	−0.248(0.164)	1.075(0.066) ***	−0.103(0.046) ***
Household size	−0.017(0.045)	1.820(0.953)	−1.699(0.982) **
_cons	−0.815(0.556)	20.712(2.193)	17.453(1.975)
/lns0	1.742 (0.055) ***		0.003 (0.156) ***
/lns1	1.656 (0.090) ***		−0.444(0.678) ***
/r0	0.159 (0.282) ***		0.239(0.807) ***
/r1	0.435 (0.277) ***		0.830(1.034) ***
sigma0	5.710 (0.313) ***		2.734(0.983) ***
sigma1	5.237 (0.472) ***		−0.104(0.047) **
rho0	0.158 (0.275) ***		0.442(0.665) ***
rho1	0.410 (0.230) ***		0.239(1.053) ***
LR Prob > chi2	0.0002		2.736(0.887)

Significant at.
*** $p<0.01$,.
** $p<0.05$,.
* $p<0.1$. Robust standard errors in parentheses.

compatible with the studies of Sarma & Rahman [40], Assaye et al. [41] and Onumah et al. [42], who have revealed schooling as a declining productivity feature. In explaining variations in rice productivity, the coefficients of farm size and household size are both positive and statistically significant. It is in accordance with both Sisang & Lee [31] and Kaloi et al. [43] which have demonstrated that farm-scale positively affects crop productivity. Such results also corroborate the results of Omodara et al., [44]; Abdallah [45], which has found a favorable association between farm size and yield. Rice production is therefore projected to increase dramatically when rice farmers have ample land to grow.

Regarding the farmers' profitability data presented in Table 1.13 the size of the farm, the farmers' experience in farming, their age, and the number of years spent in education all showed a positive and statistically significant correlation with the rice profitability of VSLA farmers. For every unit of increase in their farm size, farming experience, age and education level, their probability of rice profitability increased. This outcome aligns with the discoveries of Sisang & Lee [31], Anki [46], and Musa et al. [47] in comparable research, indicating that factors such as farm size, farming experience, and age are all positively and significantly correlated with participation in credit programs.

For non-participant farmers, farm size and harvest method had a positive and significant effect on their farm profit. Farmers who had large farm size experienced rice profitability increment. For every increase in farm size unit, their crop productivity increased and consequently their rice profit. This increase is significantly lower than that earlier observed for VSLA farmers. This result agrees with the findings of Kijima et al. [48], Wordofa et al. [49], Wu [50], and Sisang & Lee [31] and can be justified by the fact that adopting farmers had a comparative advantage of participation over non-adopting households as confirmed by the significance level of variance coefficient (*rho* 1). However, *rho* 1 for productivity and *rho* 1 rice profit all have the same signs indicating that all the farmers had above-average productivity and farm profit whether or not they adopted however they are better off being adopters of the VSLA.

3.2.6. Endogenous switching regression (ESR) on crop profitability

The results of the ESR estimation on the crop profit are presented in Table 1.10. The data set was appropriate to be analyzed using the ESR model as confirmed by the LR test which is significant at 1%. The outcome equations from the ESR show that the farm profit of adopting farmers was positively and significantly affected by farm size, farming experience, age, and farmers' education level. Household size had also a positive and significant effect on the farm profit of adopters. This could be attributed by the fact that increase in household size is likely to influence family labor positively and consequently farm profit. Non-participants had their farm profit positively and significantly determined by farm size as well. Additionally, harvest method had a positive and significant effect on their farm profit. However, level of education negatively and significantly reduced their farm profit. The positive correlation coefficients observed in both regimes provide confirmation that the hypothesis of non-selection bias can be rejected. Specifically, the coefficient was found to be statistically significant for regime 1 but not for regime 2, suggesting that households that adopted the farming practices had a notably higher farm profit in comparison to those who did not adopt VSLA. The presence of a significant (rho) value in regime 1, as opposed to regime 2, demonstrates that adopting households possessed a comparative advantage over non-adopting households.

Table 1.13
Endogenous switching regression on farmers' farm profitability .

Variables	Selection Equation	VSLA participant	Non-Participant
Farm size	0.041 (0.146)	635,700.4 (28,775.91) ***	485,578.5 (37,948.74) ***
Land-ownership	0.101 (0.141)	−4651.193 (32,457.94)	14,295.08 (44,223.34)
Main occupation	0.356 (0.156) **	38,212.23 (34,825.14)	66,687.89 (54,046.66)
Harvest method	−0.251 (0.178)	42,600.31 (43,714.07)	109,900.1 (53,491.18) **
Farm-experience	−0.037 (0.011) ***	1877.026 (2425.36) ***	−1774.722 (2558.703)
Sex	0.288 (0.151) *	3210.008 (55,994.272)	21,530.584 (41,120.013)
Age	0.030 (0.008) ***	11,087.045 (10,097.561) **	47,651.015 (72,381.06)
Marital status	0.103 (0.161)	−27,421.089 (17,261.215)	−13,567.388 (−39,241.002)
Education level	−0.217 (0.151)	60,453.078 (3240.244) ***	−37,860.511 (5059.821) **
Household size	−0.028 (0.044)	13,708.585 (31,416.003) **	−15,459.189 (6789.465)
_cons	−0.605 (0.533)	88,719.69 (93,164.8)	119,527.7 (99,276.81)
/lns0	12.700 (0.022) ***		
/lns1	12.109 (0.059) ***		
/r0	0.690 (0.166) ***		
/r1	0.023 (0.475) ***		
sigma0	327,800.9 (7299.782) ***		
sigma1	181,430.4 (10,724.48) ***		
rho0	0.598 (0.107) ***		
rho1	0.023 (0.475) ***		
LR Prob > chi2	0.0000		

Significant at.
*** $p<0.01$,.
** $p<0.05$,.
* $p<0.1$. Robust standard errors in parentheses.

3.2.7. ESR-based average treatment effect on the treated and non-treated

The model estimated the mean outcomes of the treated farmers and the corresponding counterfactual outcomes. It answered the question about the crop productivity and profitability that would have been achieved if the farmers had not received the treatment. The average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) were calculated. The estimation demonstrates that the treatment effect of VSLA adoption on crop productivity and crop profitability is positive and statistically significant from zero. The ATT is

612,535.00 TZS/ha and 1.4169Kg/ha for crop profitability and productivity respectively, as presented in Table 1.14.

Farmers' participation in the VSLA significantly improves productivity and crop profitability by 4.5% and 93.3% respectively. If the non-participants of the VSLA inclusion decided to adopt the microfinancing mechanism, their crop productivity and profitability would have increased by 21.6% and 55.4% respectively. Analysis of predictors from the endogenous switching regression identifies the group-specific factors for both participants and non-participants of the VSLA financial inclusion. For farmers who adopted VSLA, their age, education level, farm size, farming experience and household size affected their adoption decisions positively. As the farmers became older, their probability of accepting the technology increased. Age comes with more wisdom and it's believed that older farmers had more experience to enable them to compare technologies and decide on trying new ones. The numbers of years spend in school had a positive effect on the adoption of the VSLA. This can be due to the numerous advantages that education expose farmers to useful knowledge and skills that amplify their understanding of different agricultural technologies such as VSLA that enables to purchase useful inputs for enhancing agricultural productivity and consequently profitability. Farm size equally had a positive influence on VSLA participation. This can be explained by the fact that farmers with larger farms find it easy to adopt new financial inclusions such as VSLA that avail credit to facilitate the purchase of inputs and hiring of labor and machines, and this helps to keep the crop cycle going even after harvesting. These five factors were therefore observed as being positively and statistically significant on VSLA adoption. These findings were coherent with the previous findings of Fadeyi et al. [51], Dube-Takaza et al. [52], Achukwu et al. [53], and Sisang & Lee [31], Kadipo Kaloi et al. [54], Fowowe [55], and Izuchukwwu [56], who identified these characteristics to have a positive and significant influence on rice farmers' decisions to adopt new rice and other agricultural technologies.

4. Conclusion and recommendations

This paper assessed the contribution of VSLA participation on rice productivity and farm profit for smallholder rice farmers in the Mvomero district, using propensity score matching and endogenous switching regression model. The result from propensity scores matching shows that VSLA participation has a positive and significant effect on rice productivity and profitability. This is evidenced by the results from the three matching methods, which are nearest neighbor matching, radius/caliper matching, and kernel matching, which show that, on average, VSLA participants have more yield and income than non-participants. This implies that VSLA participation improved rice productivity and profitability of smallholder rice farmers through easy access credit which were used to purchase recommended inputs, technologies and support timely farm management. Moreover, the larger proportional of the population who are employed in agriculture are women and the participants of VSLAs majority are women. Therefore, promoting participation in VSLAs will help large portion of smallholder farmers mostly women to access credit and improve their farming practices, which will have multiple effect in the households, agriculture sector and economy.

The application of two econometric models effectively minimized the potential effect of selection bias arising from both observable and non-observable characteristics. This approach resulted in robust estimations of the desired parameters. The outcomes derived from these models remained consistent and reliable. Although there were variations in the adoption effects indicated by the results, either model could be chosen for a single analytical approach. However, in most studies, both models were employed based on the available data. In this study, the endogenous switching regression model, for instance, offered specific insights into the correlation of explanatory variables on various outcome measures. Additionally, it provided a counterfactual analysis of the adoption's effects. The findings revealed a significant increase in yield and profit for rice farmers in the study area upon adopting improved varieties. Given these crucial observations, the study proposes the following recommendations based on its findings.

Therefore, this study recommended that the VSLA model need to be supported and promoted by the private sector in collaboration with the government so that it can be more efficient in serving smallholder farmers in the rural areas. To ensure sustainability, the model should be established and promoted beyond the project and program level, where after the implementation period, the associations remain without proper guidelines. Also, there is a need to enhance and replicate the VSLA methodology for smallholder farmers and women in other districts and crops within the country, particularly in the rural and marginalized communities, to help them mobilize savings and obtain credit in a proper and affordable way. Finally, financial inclusion as VSLA play a very important role in improving crop yields and subsequently farmers' income and well-being. This study has presented a clear picture of the significant contribution of such technologies in the study area. Equally, the government and private stakeholders are encouraged to devise other financing mechanisms to finance the development and introduction of other improved and adaptable small-scale farm technologies that will not only boost the yields and profit of farmers but that will significantly contribute to alleviating poverty and ending hunger in the country.

CRediT authorship contribution statement

Rozalia P. Mtenga: Writing – review & editing, Visualization, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Anthony Funga:** Writing –

Table 1.14
Endogenous switching regression-based average treatment effects of VSLA participation on productivity and farm profitability.

Outcome Variable	Label	Farmers' Decision Y1(Choose to participate)	Y1(Choose not to participate)	Treatment Effect	Effect%
Rice farm profit (TZS)					
Participated	ATT	3356,025.00	2,743,490.00	612,535.00***	4.5
		(−206,190.00)	(−181,915.00)	(−24,275.00)	
Not participated	ATU	2,853,390.00	2,238,425.00	614,965.00***	21.6
		(−233,325.00)	(−207,795.00)	(−25,530.00)	
Heterogeneity	ATH	502,635.00	185,050.00	317,585.00	
Effect		−23,640.00	−17,595.00	−6045.00	
Rice Productivity/Yield (Kg/ha)					
Participated	ATT	22.3735	20.9566	1.4169***	93.3
		(1.3746)	(1.34661)	(0.1092)	
Not participated	ATU	19.0226	19.5895	−0.5669***	55.4
		(1.5555)	(1.5853)	(0.1007)	
Heterogeneity	ATH	3.3509	1.367	1.9838	
Effect		(0.1576)	(0.1573)	(0.1486)	

Note: Figures in parentheses denote the standard errors. *** and ** respectively denote significance levels at 1% and 5%.

review & editing, Visualization, Validation, Supervision, Conceptualization. **Michael Kadigi:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Data curation, Conceptualization.

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.

Data availability

The authors do not have permission to share data.

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