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Adoption and impacts of improved beehive technologies in the miombo woodland of Tanzania

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This paper analyzes the adoption and impacts of improved beehives on households' income using cross-sectional data sourced from a sample of 198 beekeepers in western Tanzania who adopted improved beehives. Propensity score matching and the endogenous switching regression model are used to assess the adoption and impacts. Results show that the adoption of improved beehives resulted in significant increase in beekeepers' income. An analysis of the determinants of adoption revealed age of the household head, years of formal schooling, access to credit, access to extension services, training and experience in beekeeping as key factors influencing the adoption. There is a need to promote the use of improved beehives so as to enhance productivity and boost income among small-scale beekeepers. Efforts to improve access to and use of improved beehives technologies should be part and parcel of income poverty reduction strategies in the study areas where beekeeping is a key livelihood activity but adoption is low. Policies that enhance the diffusion and adoption of improved beehives should be central to income poverty reduction strategies in Tanzania.

Keywords: improved beehives, adoption, endogenous switching regression, propensity score matching, households' income

Introduction

In Tanzania and other countries within miombo woodlands, beekeeping is vital for concurrent achievement of poverty reduction and forest conservation goals. However, attaining the dual goals from beekeeping depends on adoption of improved beekeeping technologies such as improved beehives, protective gear, smokers and honey extractors (Girma et al. 2008; Kuboja, Isinika, and Kilima 2017). Hence, it is important to replace traditional beekeeping because these practices are associated with low productivity (Adgaba et al. 2014; Miklyaev, Jenkins, and Barichello 2014; Yadeta 2015) as well as negative impacts on forests and woodlands due to improper use of fire that causes wildfires and bark beehives that kill trees in forests and woodlands (Augustino, Kashaigili, and Nzunda 2016). There is evidence showing that about 272,900 trees in north-western Zambia are debarked every year for making traditional beehives (Campbell et al. 2008). Unlike traditional beehives, improved beehives have no repercussions on forests and woodlands and are compatible with recommended land uses (Jacobs et al. 2006; Mwangi, Meinzen-Dick, and Sun 2011; Yirga et al. 2012). Furthermore, improved beekeeping is more productive than traditional beekeeping technologies (Mwakatobe and Mlingwa 2010).

Following the implementation of the National Beekeeping Policy of 1998 (MNRT 1998), different national and international institutions have been promoting improved beekeeping technologies in Tanzania. The major goals of these interventions are to reduce poverty while also enhancing environmental conservation. Over the last two decades, several studies have assessed the adoption of improved beekeeping technologies in Africa. Low adoption rates have frequently cited uncertainty among potential adopters regarding benefits vis-à-vis costs of adoption (Mujuni, Natukunda, and Kugonza 2012). The uncertainty relates to beekeepers' inability to afford the cost of adoption and inadequate knowledge on how to use the technology. However, there is limited empirical evidence regarding the adoption and impacts of improved beekeeping technologies such as improved beehives, protective gear, smokers and honey extractors in Tanzania. With the exception of the study done by Nkojera (2010), other studies on the adoption of improved beekeeping technologies in Tanzania (Kimaro et al. 2013; Namwata, Mdundo, and Malila 2013) have relied on descriptive statistics without application of robust statistical models to compare the performance of adopters and non-adopters. These studies have also relied on single econometric models; hence they fail to account for counterfactual effects in estimating the level of the impacts. Consequently, there is limited understanding of the statistical validity of the factors suggested either to constrain or incentivize adoption of the improved beekeeping technologies. Against this background, this study focused on adoption and income poverty impacts of using improved beehives among beekeepers in Tabora and Katavi regions where estimation was done using propensity score matching (adoption) and the endogenous switching treatment effect model which account for selection problem and unobservable effects.

Theoretical constructs and analytical techniques

Adoption of technologies

Over 95% of the small-scale beekeepers in Tanzania use log and bark hives (Lalika and Machangu 2008). The use of log (Figure 1) and bark hives (Figure 2) are traditional practices which are locally perceived to be convenient because of the abundance of miombo woodlands which provide easily obtainable raw materials for producing beehives. In spite of high usage of traditional

Figure 1: Log beehive (traditional).

beehives among small-scale beekeepers, few of them are using improved beehives. In the context of this study improved beehives comprise transitional and commercial beehives. The transitional beehives are man-made beehives at the intermediate stages between the traditional and improved hives. Transitional beehives include the Tanzanian top bar (Figure 3) and box hives (Figure 4). The transition from traditional to improved beehives has fostered the commercial honey production leading to emergence of large-scale beekeepers. However, more growth could be realized through wider adoption of commercial beehives which have a bigger laying area (brood foundation). The commercial beehives are often used by large scale beekeepers for commercial purpose. Longstroth (Figure 5) is the most popular commercial beehive in Tanzania.

The approach used to assess beekeeper decision to adopt improved beehives as well as factors affecting its adoption was the use of discrete choice models based on random utility theory (Becerril and Abdulai 2010). In this case, a beekeeper was assumed to adopt improved beehives depending on their perceived benefits referred to as utility. Thus, if we assume $p*$ to represent the

Figure 2: Bark beehive (traditional).

Figure 3: Tanzania top bar beehive (Transitional).

difference between the utility from adopting (U_{iA}) and the utility from not adopting (U_{iNA}) of improved beekeeping technologies; then an individual i will only choose to adopt a technology if $P^* = U_{iA} - U_{iNA} > 0$. This model can be expressed as follows:

$$\text{with } P_i = \begin{cases} 1 & \text{if } P_i^* > 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where P is a binary dummy variable for the use of improved hives; $P = 1$ if the technology is adopted and $P = 0$ otherwise; α= vectors of parameters to be estimated; X= a vector that represents household and farm level characteristics and ε= the random error term which accounts for factors affecting utility of improved beehives and other unobservable factors.

The adoption of improved beekeeping technologies is assumed to increase productivity as well as household income accrued from beekeeping. Assuming the outcome variable of interest (profit generated from beekeeping) is a linear function of a dummy variable for improved beekeeping technology use along with a vector of other explanatory variables; the relationship is

Figure 4: Box beehive (Transitional).

Figure 5: Langstroth beehive (Commercial).

defined as presented in equation (2).

$$Y_i = \beta Z_i + \delta P_i + \mu_i \quad (2)$$

where Y_i represents income generated from beekeeping, P is an indicator variable for adoption as defined above, β and δ are vectors of parameters to be estimated, and μ is an error term. Thus, the impact of adoption on the outcome variable is measured through estimation of δ with an assumption that the technology (i.e. improved beehives) was randomly assigned to adopters and non-adopters.

Determinants of technology adoption

The decision whether to adopt or not to adopt a technology is often a discrete choice. Discrete choice econometric models have widely been used to estimate models that involve discrete economic decision-making processes (Guerrem and Moon 2006). The use of qualitative responses such as tobit and probit models has been recommended for adoption studies. However, the use of the probit model over the logit model is sometimes rejected on the grounds that it leads to inefficient estimators and that the estimated probabilities are not constrained to lie between 0 and 1 as demanded by the probability theory (Kipsat 2002). On the other hand, the probit has an advantage over logit specification when sample size is less than 1000. Thus, with a sample size of 198 beekeepers, the present study adopted a probit model to examine determinants of beekeepers' decision to use or not to use improved beehives. Initially explanatory variables included in the model were checked for the existence of multicollinearity. The test showed that there was no separate collinearity among the explanatory variables. There was an association between access to extension services and contacts with extension officers; and between access to credit and use of credit in beekeeping. Looking into their contribution to the estimated model, contact with extension officers and use of credit in beekeeping in relation to other enterprises were dropped from the analysis. Eventually the empirical probit model used to estimate the adoption of improved beehives among beekeepers was specified as:

$$\begin{aligned} AD = {} & \beta_0 + \beta_1 Age + \beta_2 Sex + \beta_3 Hhz + \beta_4 Credit \\ & + \beta_5 Train + \beta_6 Exp + \beta_7 Mkt + \beta_8 \mathrm{Reg} \\ & + \beta_9 Edu + \beta_{10} Ext \end{aligned} \quad (3)$$

where *AD* takes the value of one for adopters or zero for non-adopters, *Age*= age of the household head (years), *Sex*= sex of the household head ('1' male and '0' female), *Hhz*= household size, *Credit*= access to credit ('1' access to credit and '0' otherwise), *Train*= training on improved beekeeping practices ('1' access to training and '0' otherwise), *Exp*= experience in beekeeping (years), *Mkt*= access to markets ('1' access to markets and '0' otherwise), Re*g*= region of residence of beekeepers ('1' Tabora and '0' Katavi), *Edu*= number of years of schooling, *Ext* = access to extension services ('1' access to extension services and '0' otherwise) and $\beta s$are coefficients to be estimated.

Estimation of impacts of adopting improved technologies

As opposed to experimental studies, in non-experimental studies one does not observe the outcome variables of household that adopt, had they not adopted a technology. In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control groups, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of households, but rather to the household itself deciding to adopt given the available information. The adopters and non-adopters may therefore be systematically different with respect to some variables (Amare, Asfaw, and Shiferaw 2012).

Several studies on adoption of crop technologies (Kalinda and Tembo 2010; Langyintuo and Mungoma 2008; Mason, Jayne, and Mofya-Mukuka 2013; 2014) and a few on the beekeeping industry (Adgaba et al. 2014; Gorfu 2005; Mujuni, Natukunda, and Kugonza 2012; Nkojera 2010; Wodajo 2011) have utilized single econometric models such as correlated random effects (CRE), tobit, double hurdle and other fixed-effect models. The disadvantage of using a single model is that the estimates are not robust enough because each model has its own limitations which cannot be individually corrected. Unlike most of the previous studies, this paper used two different econometric approaches: the endogenous switching regression (ESR) model and PSM to analyze the impact of using improved beehives in Tanzania.

Endogenous switching regression

The overall objective of this study was to estimate what impact use of improved beehives had on outcome variable in this case is the households' income generated from bee-keeping. This can be expressed as follows:

$$Y_i = \begin{cases} Y_i^T & \text{if } T_i = 1 \\ Y_i^C & \text{if } T_i = 0 \end{cases} \tag{4}$$

Household using improved beehives is referred to as 'treatment' and is indicated by the 'treatment' as dummy:

$$T_i = \begin{cases} 1 = \text{adopter} \\ 0 = \text{non-adopter} \end{cases}$$

Thus, in order to estimate the effect of using improved beehives, the difference in terms of profit generated between beekeeper using improved beehives (Y_i^T) and the very same beekeeper at the same time if had not used improved beehives (Y_i^C) need to be computed. The computation can be realized as follows:

$$\text{Treatment Effect} = Y_i^T - Y_i^C \tag{5}$$

However, practically this cannot happen whereby same individual can be observed in the two scenarios (with and without the treatment) at the same time. This implies that for any individual at any given time, the counterfactual situation cannot be observed. The only solution of this is to find out individuals in the treatment group that will be compared with identical individuals from the control group. This provides the average difference in the outcome variable across the entire population and it is referred to as the average treatment effect (ATE).

$$ATE = E[Y_i^T - Y_i^C] \tag{6}$$

This derived figure represents the effect of the treatment on the total target population, if and only if three assumptions hold. These assumptions are that the observed outcomes come from a population that represents the total target population; the treatment (adopters) is the same as the control (non-adopters) population in all manners (except the treatment); and that the treatment status of an individual does not affect the outcome of any other individual as well as that the treatment received is uniform to all individuals. Based on these assumptions, estimating ATE is still challenging as it is difficulty all three assumption to hold true. However, without having a representative population of the treatment group and control group being selected randomly from the total target population, the average treatment effect on the treated (ATT) can be estimated. This is what is referred to as the impact of the treatment on the treated group. Estimated ATT under this case still requires comparing identical individuals from the two groups (treatment and control) otherwise the expected treatment effect on the outcomes will be affected by selection bias.

In the majority of cases, PSM is the method used most often to calculate the ATT. However, this fall shortcoming of accounting for unobservable factors that affect the adoption process and also it assumes that the coefficients of independent variables for adopters and non-adopters are similar of which is not the case (Asfaw et al. 2012; Di Falco, Veronesi, and Yesuf 2011; Shiferaw et al. 2014; Teklewold, Kassie, and Shiferaw 2013).

Alternatively, the endogenous switching regression (ESR) framework has been used to estimate the average treatment effect of the treated (ATT) and of the untreated (ATU) by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios (Di Falco, Veronesi, and Yesuf 2011; Khonje et al. 2015; Shiferaw et al. 2014). Manda (2016) in his PhD study used the ESR framework to estimate the impacts of adopting improved maize varieties on the welfare of a set of farmers in Eastern Zambia. This study also adopted a similar estimation regression model to calculate the ATT and ATU, as was used by Manda (2016) as follows:

Adopters (observed in the sample)

$$E(y_{i1}/T = 1; x) = x_{i1}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i1} \tag{7a}$$

Non-adopters (observed in the sample)

$$E(y_{i2}/T = 0; x) = x_{i2}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i2} \tag{7b}$$

Adopters had they decided not to adopt (counterfactual)

$$E(y_{i2}/T = 1; x) = x_{i1}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i1} \tag{7c}$$

Non-adopters had they decided to adopt (counterfactual)

$$E(y_{i1}/T = 0; x) = x_{i2}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i2} \tag{7d}$$

The average treatment effect on the treated (ATT) is computed as the difference between (7a) and (7c);

$$\begin{aligned} ATT &= (y_{i1}/T = 1; x) - (y_{i2}/T = 1; x), \\ &= x_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon} 2) \end{aligned} \tag{8}$$

The average treatment effect on the untreated (ATU) is given by the difference between (7d) and (7b);

$$\begin{aligned} ATU &= (y_{i1}/T = 0; x) - (y_{i2}/T = 0; x), \\ &= x_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon} 2) \end{aligned} \tag{9}$$

The expected change in the mean outcome of adopters when they had similar characteristics to non-adopters or vice versa, are captured by the first term on the right of equations (8) and (9). The second term (λ) is the selection term that captures all potential effects of the difference in unobserved variables.

Assessing impact of improved beekeeping technologies on households' income

The relationship between adoption of improved beekeeping hives and households' annual income from beekeeping as an outcome variable is theoretically complex (Amare, Asfaw, and Shiferaw 2012). Taking into account these complexities and pit falls in impact evaluation; this study estimated the impact of improved beehives on households' annual income in terms of profit accrued from beekeeping using both PSM and ESR. The use of PSM needs a choice of matching algorithm to be used. However, according to Caliendo and Kopeinig (2008) all matching algorithms have their own drawbacks. In small samples, a choice of the matching algorithm is important to ensure comparison of only exact matches. Thus, in view of the data set used, in which there was a larger number of untreated than treated individuals, the nearest neighbour and kernel matching algorithms were used to match treated units with similar representatives within the untreated sample. The nearest neighbour matching (NNM) algorithm was used as it gives good quality matching and decreases bias as it matches with replacement (Apel and Sweeten 2010; Gemici, Rojewski, and Lee 2012). The kernel matching was used because it allows more information to be used for construction of a counterfactual outcome, as it uses weighted averages of all individuals in the control group (Caliendo, Hujer, and Thomsen 2008).

Study design and data collection

Data used in this study were collected from a sample of 198 households; 60 from Katavi and 138 from Tabora regions during the 2016/2017 harvesting season. Out of 60 respondents in Katavi region, 90% were male and 10% were female; whereas in Tabora region out of 138 respondents, 97.8% were male and only about two percent were female. The two regions are found within the western miombo woodland in Tanzania where many of the rural communities rely on tobacco production as their main source of income. Beekeeping is also practiced in locations with abundant miombo woodlands which are found in Sikonge, Uyui, Urambo and Kaliua Districts in Tabora Region; and Mpanda, Mlele and Nsimbo Districts in Katavi Region. The miombo woodlands are particularly suitable for beekeeping as they provide excellent bee forage. According to Monela and Abdallah (2007), *Julbernadia globiflora*, and *Brachystegia spp* were the best nectar producing trees. Others were *Brachystegia spiciformis* and *Zanthoxylum chalybeum*. Also, the presence of other bees' forage species such as *Dombeya burgessiae*, *Maesa lanceolata*, *Diospyros whyteana*, *Uapaca kirkiana*, *Vitex mombassae* and *Mysalicifolia spp* significantly supports the honey industry (Monela and Abdallah 2007). During the first stage, districts in each region were stratified according to honey production levels; thereafter, three districts from Tabora Region and one district from Katavi Region were purposively selected to form the study area.

A total of 198 households were randomly selected from the sampling frame of all beekeepers in the study area. The sampling frame of beekeepers was generated before the main survey in collaboration with District Beekeeping Officers. A questionnaire was used to collect information from households through personal interviews whereby beekeepers reported different information with regards to beekeeping. The data included information on farmers' patterns of resource use, technology choices, production of different bee products from both traditional and improved beehives, total number of beehives owned as well as number of beehives harvested, quantity of honey and bee wax harvested, size of beehives, inputs and outputs prices, socioeconomic profile of beekeepers along with their access to extension, credit services and trainings opportunities. Productivity of traditional and improved beehives was measured in terms of litres of honey per hive. The data were processed and analyzed using STATA Version 14.2 which is statistical software for data analysis. The software was used to examine determinants of adoption of improved beehives as well as estimating the adoption impacts using PSM and ESR regression models.

Results and discussion

This section presents findings and discussion of the study. It comprises three main sub-sections. These include socioeconomic characteristics of the respondents, determinants of technology adoption and impacts of improved beekeeping on households' annual profit from beekeeping.

Socioeconomic characteristics of the respondents

Table 1 shows descriptive statistics of different variables by region and adoption category of improved beehives. Result shows that both adopters and non-adopters in the two regions had a mean age of around 50 years. This result implies that many beekeepers are within the productive age category. Adopters and non-adopters supported an average of 7 people per household. Also, results show that adopters are different from non-adopters in terms of household characteristics such as education (years of schooling), experience in beekeeping, productivity of beehives and profit from beekeeping. Education is hypothesized to have a positive impact on technology adoption. The level of education measured in terms of years of schooling was higher for adopters than non-adopters in both regions; it ranged from 7 to 8 for adopters whereas for non-adopters it ranged from 5 to 6 years. Education enables them to understand better the importance of adopting improved beekeeping hives. In terms of years of experience in beekeeping, adopters in Tabora Region had less experience than their fellows in Katavi Region.

In both Tabora and Katavi Regions productivity of improved beehive was higher than traditional beehive. However, productivity of improved beehive varied within adopters; for instance, adopters in Katavi Region realized higher productivity (14.29 litres honey/hive) than in Tabora Region (11.1 litres of honey/hive). Similar trend in productivity among adopters was also observed in beeswax. Even non-adopter using traditional beehives in Katavi Region recorded higher productivity of honey (i.e. about 8.98 litres /hive) than their counterparts in Tabora Region who recorded 6.91litres/hive. In both districts, adopters using improved beehives realized less profit from beekeeping than non-adopters. These findings conform to that of Kuboja, Isinika, and Kilima (2016) who reported a higher net farm income for beekeepers using traditional beehives than those using improved beehives (Table 1). However, it is worth noting that this comparison was based on un-matched samples and there are

Table 1: Socioeconomic characteristics of the sample households by region and adoption status.

Region	Adoption category	Variables	n	Minimum	Maximum	Mean	Std. Deviation
Katavi	Non-adopter	Age of the household head	46	29.00	78.00	49.17	12.42
		Total number of household member (family size)	46	2.00	12.00	5.69	2.61
		Experience in beekeeping (years)	46	3	40	13.04	11.39
		Total number of traditional beehives owned	46	.00	500.00	58.72	102.25
		Productivity of traditional beehive (litres of honey/hive)	34	2.85	16.92	8.98	3.52
		Total profit from beekeeping (TZS)	46	0	8664750.00	1265648.10	2025955.30
		Years of schooling	46	.00	13.00	5.0870	4.16
	Adopter	Age of the household head	14	30.00	75.00	52.28	12.63
		Total number of household member (family size)	14	3.00	11.00	6.57	2.38
		Experience in beekeeping (years)	14	4	40	15.21	12.28
		Total number of improved beehives owned	14	4	500	59	131.88
		Productivity of improved beehives (litres of honey/hive)	14	5.70	20.00	14.29	5.55
		Total profit from beekeeping (TZS)	14	57950.00	8523479.40	923802.80	2239728.40
		Years of schooling	14	6.00	11.00	7.36	1.22
Tabora	Non-adopter	Age of the household head	116	24.00	85.00	53.43	15.93
		Total number of household member (family size)	116	1.00	15.00	6.97	3.04
		Experience in beekeeping (years)	116	2	60	19.41	18.91
		Productivity of traditional beehive (litres of honey/hive)	62	.67	18.75	6.91	4.01
		Total profit from beekeeping (TZS)	116	0	6491032.00	657381.50	1366286.90
		Years of schooling	116	.00	14.00	6.6810	2.57614
	Adopter	Age of the household head	22	28.00	81.00	51.68	13.61
		Total number of household member (family size)	22	3.00	15.00	7.00	3.08
		Experience in beekeeping (years)	22	2	20	7.14	5.91
		Total number of traditional beehives owned	22	.00	200.00	42.68	51.30
		Total number of improved beehives owned	22	2	160	33	42.48
		Productivity of improved beehive (litres of honey/hive)	22	3.00	20.00	11.10	5.25
		Total profit from beekeeping (TZS)	22	27486.80	3255210.00	609742.20	771807.80
		Years of schooling	22	7.00	14.00	8.41	2.72

reasons to doubt whether it leads to a balanced number of cases and controls across the levels of the selected matching variables. This comparison may wrongly be interpreted to mean no impact of adopting improved beehives on households' income. We reconcile this view through matched comparisons in section 4.3.

Overall, out of 198 respondents, 189 were male and the rest 9 were female. About 22% of the females were adopters while 78% were non-adopters. For males, 18% were adopters against 82% who were non-adopters. Adopters in both regions had better access to extension services, credit, training on beekeeping practices and market and marketing information than non-adopters. To assess if there was an association between each of these dummy variables with the adoption status, the Pearson Chi-Square test was conducted to determine if the two variables under consideration are independent. Results of the Chi-Square test given in Table 2 indicate that access to extension services, credit, market and marketing information as well as training on improved beekeeping practices had a significant effect on adoption level of improved beehives across the study area. Thus, we reject

Table 2: Chi-square statistics to test for effects of different variables on adoption of improved beehives.

Region	Variable	Chi-Square value	df	Asymp.Sig. (2-sided)
Tabora	Access to extension services (1=yes, 0=no)	35.768	1	.000
	Access to credits (1=yes, 0=no)	25.148	1	.000
	Access to market and marketing information (1=yes, 0=no)	15.552	1	.000
	Access to training on beekeeping (1=yes, 0=no)	37.776	1	.000
Katavi	Access to extension services (1=yes, 0=no)	22.319	1	.000
	Access to credits (1=yes, 0=no)	29.814	1	0.000
	Access to market and marketing information (1=yes, 0=no)	8.673	1	.003
	Access to training on beekeeping (1=yes, 0=no)	29.376	1	.000

the null hypothesis that the variables are independent and gain confidence in the alternative hypothesis that they are in some way related. Therefore, these variables are important for adoption of improved beehives.

Hence, institutional support services such as extension services and financial services are important in the dissemination of new technologies because they have positive impact on the adoption of improved beehives. However, it is worth noting, that the descriptive results are only indicative of the impacts of the technology considered. Thus, the empirical analysis that follows, aims at providing more formal and conclusive evidence of the adoption impacts of improved beehives in the miombo woodlands of Tabora and Katavi Regions, western Tanzania.

Factors underlying adoption of improved beekeeping technologies

The estimated parameters of the probit model of adoption of improved beehives are presented in Table 3. The goodness-of-fit measurements of the model are also given in Table 3. The likelihood ratio index confirms that 72% of the total variation in dependent variable was accounted for by the independent variables in the fitted model. The computed log likelihood ratio exceeds the Chi-square critical values at 1% significance level, confirming that the independent variables jointly influence the adoption of improved beekeeping technology. Overall, six variables were found to have positive and significant effect on the adoption of improved beehives; whereas only one variable was found to have negative and significant effect on the adoption of the technology. The six variables included the following: age of the household head, access to credit, training on beekeeping practices, and access to markets; number of years of schooling and access to extension services. Experience in beekeeping was the only coefficient which had a negative and significant effect on the adoption. This is consistent with the expectation that the probability of adopting improved technologies such as improved beehives increases with access to markets, credit, training, extension services, age and years of schooling.

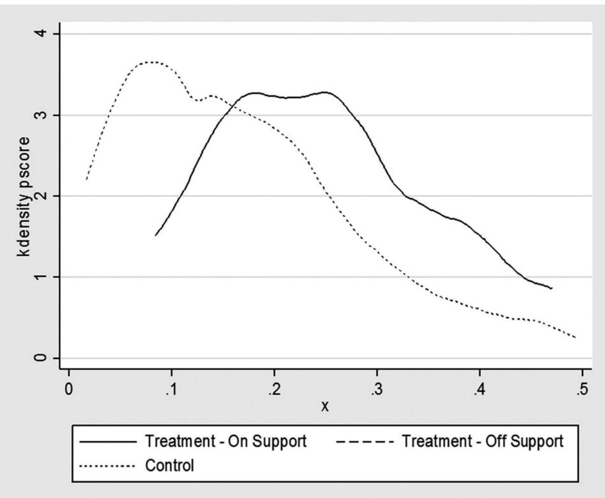

Figure 6: Propensity score distribution and common support for propensity score estimation.

These findings are in line with that of Adgaba et al. (2014) and Wodajo (2011) who found a positive and significant influence of education on adoption of improved beehives among beekeepers in the Kingdom of Saudi Arabia and Ethiopia, respectively. Results further show that access to extension services increases the likelihood of adopting improved beehives. Beekeepers that are regularly visited by extension workers are likely to adopt improved beehives due to their increased exposure and awareness. Similar results were also found for the adoption of improved beehives in Mpanda district in Tanzania (Nkojera 2010), Ethiopia (Gebremichael and Gebremedhin 2014; Gorfu 2005) and Bushenyi district in western Uganda (Mujuni, Natukunda, and Kugonza 2012). Also, access to credit and training on beekeeping practices had a significant influence on adoption of improved beehives in the study area. Training develops skills and knowledge among beekeepers whereas access to credit improved their capacity to invest. This result confirms similar findings by Wodajo (2011) and Nkojera (2010) who found a positive significant influence of training on adoption of improved beehives in Ethiopia and Tanzania, respectively. The positive effect of access to credit was also reported by Mujuni, Natukunda, and Kugonza (2012) in Uganda and Wodajo (2011) in Ethiopia. Increased access to institutional support services such as extension, credit and skill and knowledge building should thus be a major part of efforts aimed at promoting adoption of improved beekeeping technologies.

The result further indicates that access to markets is significant and positively affecting adoption of improved beehives. Easy access to and availability of market information plays a major role in reducing transaction costs to beekeepers in the search of markets for their products as well as inputs such as honey extractors, smokers and protective gears. Thus, if beekeepers have access to markets, then their likelihood of adopting the improved beehives is higher than non-adopters. Similar result was also reported by Gebremichael and Gebremedhin (2014) who found a significant influence of market access on the adoption of improved beekeeping hives in northern Ethiopia.

Treatment effects of improved beekeeping technologies on adopters

Propensity score matching results

Prior to estimation of the impacts of the treatment on the treated, a graphical prediction of whether there is a treatment effect or not was done by plotting the propensity scores against the treatment status (Figure 6). The treatment and the control groups overlapped yet they were clearly distinct from each other; implying that the treatment has had impact as the common support assumption was graphically verified. Also Figure 6 shows none of individual from the treated was found on the Treatment-off Support implying that the common support assumption was not violated. This is to say that there are comparable observations in the treatment and control groups to validate the comparison. Also, a balancing test of equality of means before and after the matching to evaluate if the PSM succeeded in balancing the characteristics between

Table 3: Probit estimates of the determinants of adoption of improved beehives in western Tanzania.

Variables	Coefficient	Std. Error	z	$p > \|z\|$
Age of the household head	.07	0.02	2.97	0.003
Sex of the household head	.86	0.97	0.88	0.38
Household size	.10	0.08	1.29	0.19
Access to credit	1.10	0.49	2.22	0.03
Training on beekeeping	2.50	0.57	4.37	0.00
Experience in beekeeping	−0.07	0.02	−3.14	0.002
Access to market and marketing information	.69	0.43	1.61	0.10
Region	−0.61	0.48	−1.25	0.21
Number of years of schooling	.24	0.10	2.35	0.02
Access to extension services	1.64	0.47	3.49	0.00
Constant	−9.61	2.51	−3.83	0.00
Summary statistics				
Log likelihood	−25.87			
Pseudo R^2	0.72			
Prob > Chi^2	0.00			
LR Chi^2 (10)	132.58			
Number of observations	197			

Table 4: Balancing test of explanatory variables before and after matching.

	Unmatched	Mean		t-test	
Variable	Matched	Treatment	Control	t	$p>\|t\|$
Age of the household head	U	51	52	−0.11	0.91
	M	51	51	0.29	0.77
Sex of the household head	U	0.94	0.95	−0.32	0.75
	M	0.94	0.94	−0.03	0.98
Household size	U	6.83	6.61	0.41	0.68
	M	6.83	6.68	0.22	0.83
Access to credit	U	0.83	0.15	−1.02	0.31
	M	0.83	0.08	−0.02	0.98
Access to training	U	0.61	0.51	1.07	0.29
	M	0.61	0.58	0.28	0.78
Experience in beekeeping	U	10.28	17.61	−2.45	0.015
	M	10.28	10.15	0.05	0.96
Number of years of schooling	U	7.27	6.78	0.83	0.41
	M	7.27	7.37	−0.12	0.91
Access to extension services	U	0.5	0.31	2.12	0.035
	M	0.5	0.5	−0.04	0.97
Region	U	1.39	1.28	1.24	0.22
	M	1.39	1.39	−0.02	0.98

treated and control groups was done. Since the data were collected after the intervention, only variables that cannot be affected by the intervention were used as balancing variables. Results in Table 4 show a clear imbalance between two covariates (experience in beekeeping and access to extension services) before matching. However, the differences were no longer statistically significant after matching, suggesting that matching helped to reduce the bias associated with observable characteristics. This is also confirmed in a summary of the balancing tests given in Table 5.

Results of the PSM obtained from both the nearest neighbour and kernel matching algorithms are presented in Table 6. Results show that regardless of the matching algorithm used in the estimation, adoption of improved beehives helps to increase profit from beekeeping. Using NNM and Kernel matching the average treatment effects on the treated was 535,628.50 TZS and 615,457.50 TZS, respectively. A Similar finding was also reported by Affognon et al. (2015) in Kenya where adoption of modern hives had an impact on improving honey production. Based on these findings there is a need for promoting utilization of improved beehives among non-adopters due to the fact that the use of these hives plays great role in boosting households' earnings leading to improved wellbeing.

Findings from endogenous switching regression model

Table 7 presents the ESR-based average treatment effects of adopting improved beehives on household annual profit from beekeeping under actual and counterfactual conditions. The predicted outcome variable from ESR is

Table 5: Summary of the balancing test of covariate variables.

Sample	Pseudo R^2	LR Chi^2	$p > Chi^2$
Unmatched	0.093	17.42	0.042
Matched	0.002	0.23	1.000

Table 6: PSM estimates of the impact of improved beehives adoption on annual household beekeeping income.

Matching algorithm	variable	Sample	Treated	Control	Difference	S.E	*t-stat*
NNM	Annual beekeeping profit	Unmatched	750,151.0	830,099.2	−79,948.2	295,388.5	−0.3
		ATT	750,151.0	214,522.5	535,628.5	301,927.0	1.8
Kernel	Annual beekeeping profit	Unmatched	750,151.0	830,099.2	−79,948.2	295,388.5	−0.3
		ATT	900,801.3	285,343.8	615,457.5	813,602.9	0.8

Table 7: ESR estimates of the impact of improved beehives adoption on annual household beekeeping income.

Matching alogarithm	variable	Sample	Treated	Control	Difference	S.E	*t-stat*
NNM	Annual beekeeping profit	Unmatched	750,151.0	830,099.2	−79,948.2	295,388.5	−0.3
		ATT	750,151.0	214,522.5	535,628.5	301,927.0	1.8
		ATU	830,099.2	374,567.9	−455,531.2	-	-
Kernel	Annual beekeeping profit	Unmatched	750,151.0	830,099.2	−79,948.2	295,388.5	−0.3
		ATT	900,801.3	285,343.8	615,457.5	813,602.9	0.8
		ATU	839,019.3	509,416.1	−329,603.2	-	-

used to examine the impact of improved beehives by adoption category. The model is also used to validate PSM results regarding impact assessment of the improved beehives. The ESR-based average treatment effect estimates presented in Table 5 are similar to the PSM-based estimates. The results also show that adoption of improved beehives increases households' profit from beekeeping; adopters would benefit more than non-adopters. The average increase in households' annual income from beekeeping for adopters (ATT) is 535,628.50 TZS equivalent to US$246.8 when matching was done using the NNM algorithm. For the case of kernel matching the average treatment effects on the treated is 615,457.50 TZS equivalent to US$283.6. This implies that adopters would not have gained income from beekeeping had they not adopted improved beehives. Results from both models (PSM and ESR) have similar implications. The average treatment effect on the untreated (ATU) results from ESR also indicate that non-adopters would have achieved beekeeping income gains of 455,531.20 TZS equivalent to US$168.7 or 329,603.20 TZS equivalent to US$151.9 per year had they adopted improved beehives depending on the matching algorithm used. The consistency of the findings from both PSM and ESR estimates suggests that fostering growth in the beekeeping sector and ensuring sustainable poverty reduction depend on the adoption of improved beehives of either category (transitional or commercial types). Therefore, there is a need for the government to come up with policies and strategies aiming at enhancing the adoption of improved beehives. On the other hand, the private sector needs to tape into this opportunity by facilitating access to improved beehives among small-scale beekeepers. This goal can be effectively achieved when farmers have access to soft loans to allow them finance the initial investment that was estimated to be about 100,000.00 TZS/beehive which is equivalent to around US$43 which cannot be easily afforded by poor beekeepers.

Conclusions

This paper analyzed the determinants and impacts of adoption of improved beehives on households' profit from beekeeping in western zone of Tanzania using data obtained from a sample of 198 beekeepers. The probit model estimates of the determinants of adoption of improved beehives showed that adoption is significantly related to age of the household head, years of formal schooling, access to credits, access to extension services, training and experience in beekeeping. This implies that easy access to institutional support such as extension services, financial services and capacity building would play most important role in adoption of improved beekeeping technology leading to reduced income poverty.

Using the PSM and the ESR model, the paper further shows that adoption of improved beehives leads to significant gains in beekeeping profit. The magnitudes of the estimated effects were almost similar across the two econometric methods. In view of these findings, there is a need for policies and strategies aimed at enhancing the adoption of improved hives among non-adopters. This can be achieved through more efficient extension and provision of credit as well as training and market services.

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