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Evaluation of the impact of fuelwood tree planting programmes in Tanzania

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Abstract

The rapid growth in Tree Planting for Fuelwood (TPF) program indicates the importance of taking care of the increasing demand for fuelwood globally. TPF programs in Tanzania aim to sustainably meet the rising demand for fuelwood. We evaluate the impact of TPF programs on the number of trees planted and those planted for fuelwood. Using survey data, we employ the Heckman and Propensity Score Matching techniques to estimate whether households plant trees for fuelwood and can identify tree species that would influence them to plant trees. We find positive and significant impacts of TPF programs on the number of trees planted and those planted for fuelwood. Households who participated in TPF programs have significantly more trees than their counterparts. Furthermore, we observed a positive and significant influence of TPF programs on forest policy in terms of harvesting tree products for trade, household assets, farm size, household head's age, tree species and income from selling fuelwood. Although the forest policy on harvesting is associated with households' participation in TPF programs, in practice there is no freedom to harvest and transport tree products obtained from farms, and both fuelwood from farms or natural forests both face restrictive transport tariffs. The results further indicate that households plant trees mainly to sell fuelwood. These results can be used by policymakers to promote tree planting on farms to obtain an income from fuelwood, treating it as a business opportunity. This paper makes a significant contribution to the literature due to the approaches used for estimation. Our results also suggest that fuelwood which receives less attention when it comes to sustainable energy production may need a regulatory authority like petroleum, natural gas and electricity which are regulated by the energy authority in Tanzania.

Keywords: tree-planting for fuelwood; tree planting programmes; Heckman; propensity score matching

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1. Introduction

Energy is important for economic growth [1, 2]. Knowledge concerning the standard and sustainable use of energy is not fully exhausted [3]. 'Standard' in this study refers to as a comparison point against which other energy supplied including petroleum, gas, and electricity are regulated by the Energy and Water Utilities Regulatory Authority (EWURA) in Tanzania, in terms of ‘’accessibility, licensing, promoting regulated charges, effective competition, economic efficiency and protecting the interests of all consumers’’ (Act Cap 414 of the laws of Tanzania, as cited in EWURA [5]). However, most studies have focused on non-conventional (non-traditional) energy [4] with important conventional (traditional) energy from forest biomass being ignored by most researchers [5].

Most research in developing countries focuses on modern energy [6, 7], whereas most people in developing countries depend on charcoal and firewood for cooking and heating [6, 8]. Therefore, this needs to be sustainably available to all consumers although it leads to deforestation according to various studies [9, 10].

However, fuelwood provides 80 % of fuel needs in sub-Saharan Africa countries [11] including Tanzania where over 80 % of the residents depend on fuelwood for cooking and heating [12, 13], although it caused 70 % of forest loss. According to Mwampamba et al. [14], the heavy dependence on fuelwood for cooking and trade is the major of cause of deforestation. To counteract this, TPF programmes have been introduced in developing countries [9, 15], which indicates the importance of meeting the increasing demand for fuelwood globally [16]. The literature on TPF programmes has mixed views on them and households’ involvement in tree planting for fuelwood [17–19] Tesfaye et al. [17] indicate that householders’ tree planting produces more fuelwood while reducing pressure on forests. Bhattacharya et al. [18] argue that government-sponsored tree-planting programmes are important to meet national fuelwood targets. Bhatt et al. [19] argue that extensive TPF programmes are the only option for bridging the gap between the rising demand for and a shortage of fuelwood that communities depend on.

There have been many publications on the impact of forest conservation and management programmes on fuelwood supply [20, 21], but little seems to have been published on the impact of TPF programmes, apart from the papers by Kuntashula and Mungatana [22] and Nuberg et al. [15]. The former studied the impact of TPF on natural forests, and Nuberg et al. [14] evaluated a 2-year TPF programme for the national capital district. This shows that few studies have been done on the impact of TPF programmes at household level.

This article rigorously evaluates the impact of TPF programmes on the number of trees planted for fuel, which differs from Clair [20] and Jarzebski et al. [21] that focus on the impact of forest conservation and management programmes. Our findings are helpful to the implementation of future tree-planting programmes and sustainably meet households’ demand for fuelwood, as well as helpful to forest policymakers in Tanzania and elsewhere with similar conditions.

Nomenclature

ρ	correlation coefficient of the error terms from the selection and the outcome equations
σ	estimator of the standard error of the residual in the outcome equation
λ	inverse Mills ratio
χ	Chi-Square Statistic
OLS	Ordinary Least Squares regression
N	number of observations
Z	indicator variables used to determine whether treatment is observed or not
β	coefficients obtained from the regression model(s)

2. Methodology

This study employed Heckman’s model to correct for bias due to censoring and account for endogeneity selection bias and propensity score matching (PSM) to adjust covariate distribution between programme participants and non-participants, to check for the robustness of our findings and ascertain whether they still hold as in Heckman’s model. The Heckman model is designed to resolve selection bias that may arise when selection of the sample is not randomly decided, involving two-stage approach. Several studies describe the intuition of the model as requiring a two-stage process (e.g., Kulindwa [13]). We examined the difference in the number of trees planted and those planted for fuelwood between TPF-programme participants and non-participants. Our empirical analysis is based on data from 11 villages in the Coast and Morogoro regions, randomly selected for analysis between 2014 and 2015, where tree-planting programmes are active. We also examined the difference between participants and non-participants in TPF programmes in the number of trees planted and those planted for fuelwood.

3. Results and discussion

The outcome and covariate variables of our study were age and education level of household head, household size, households planted trees for fuelwood, their income from selling fuelwood, income per capita and farm size.

3.1. Results of the Heckman and Logit models

We estimated the OLS model to observe the effect of TPF programmes when variables are assumed to be fixed and then Heckman's model that treats covariates as random and stochastic. OLS regression results of that suggest prediction error of the model needs additional investigation. If OLS omits inverse Mills term (λ), this may lead to inconsistent estimation of the coefficients. The statistical outcome of inverse λ at 1 % level of significance confirms OLS inconsistency.

Our Heckman model results indicate that the estimated selection and outcome questions (Table 1) are not independent, as justified by the Mills ratio significance. Consequently, we cannot reject the alternative hypothesis that independence of questions is not equal to zero.

Table 1. Heckman maximum likelihood estimates of households' tree planting for energy.

Variables	OLS[a]	Heckman model
	Coefficients	Coefficients
Outcome model (number of trees planted)		
Sex of household head	–3.199 (4.564)	–4.229 (6.435)
Household size	–3.243 (1.567) **	–2.097 (2.680)
Education of household head (years)	–1.166(0. 691) **	–1.513 (0.758) ***
Age of household head	0.259(0.177)	0.474 (0.258) **
Forest policy on harvesting and transporting tree products to the markets (dummy)	27.426 (14.310) **	41.019 (7.717) ***
Log of off-farm income	3.644 (1.500) ***	3.440 (2.815)
Households' farm size	2.006 (1.316)	–0.044 (2.221)
Household sells fuelwood (yes = 1, 0 otherwise)	–8.905 (60.331)	10.777 (29.990)
Log household income from selling fuelwood	4.531 (9.625)	–1.996 (5.473)
Log of value of household assets per capita (per a.e.u)	8.620 (10.299)	37.607(14.991) ***
Time taken to reach the forest reserve	–3.150 (4.111)	–3.311 (2.072)
Mills ratio	4.314 (3.198)	
Constant	29.610 (54.807)	–19.555 (8.472) **
Statistics		
Wald X^2 (14)	33.80***	
R^2	0.418	

Selection model (tree planted for energy)		
Sex of household head	–0. 016 (0.571)	0.059 (0.285)
Household size	–0.017(0.018)	–0.051 (0.114)
Education of household head (years)	–0.002(0.008)	–0.027 (0.034)
Age of household head	0.002(0.002)	0.005 (0.012)
Forest policy on harvesting and transporting tree products to the market (dummy)	0.092(0.146)	0.310 (0.319)
Log of off-farm income	0.093(0.038) ***	0.374 (.072) ***
Household head participated in tree-planting programme (yes = 1, 0 otherwise)		0.887 (0.348)***
Households' farm size	0.015(0.012)	0.068 (0.041)
Household sells fuelwood (yes = 1, 0 otherwise)	–0.295(0.273)	–3.735 (3.258)
Log household income from selling fuelwood	0.140(0.048) ***	0.987 (0.542) **
Log of value of household assets per capita (per a.e.u)	–0.261(0.139) **	–1.212(0.584) ***
Time taken to reach forest reserve	–0.010(0.052)	0.052 (0.0901) **
Mills ratio	–0.043(0.081)	–22.493(6.647) ***
Constant	1.746(0 .750) **	5.233 (3.460)
Statistics		
Wald X^2	34.75***	86.79***
ρ		0.322 (0.0676) ***
σ		3.420 (0.071) ***

Note: [a]Bootstrap standard errors with 200 replications adjusted for villages' clusters in parentheses; *, ** and *** indicate statistical significance at the 1 %, 5 % and 10 % level respectively.

The results presented in Table 1 indicate that the explanatory variables that are statistically significant and associated with the number of trees planted and those planted for fuelwood include. If household head participated in tree-planting programme, Forest policy on harvesting and transporting tree products to the market, and Household income from selling fuelwood.

3.2. Results of the PSM model

The results from estimating the propensity score across treated and untreated groups (Table 2 and Table 3) indicate that there are significant differences between households who participated in TPF programmes and non-participants before matching in nearly all the outcome variables.

Table 2. Characteristics of participants and non-participants in TPF programme before matching.

	Participants (N = 99)	Non-participants (N = 104)	Standardized Difference in mean
Sex of household head (dummy)	0.757	0.767	–0.17
Household size (number)	5.301	5.424	–0.66
Education of household head (years)	5.495	4.848	1.24
Age of household head (years)	51.476	46.525	3.16***
Number of trees planted	47.563	1.377	10.63***
Household planting trees for fuelwood (yes = 1, 0)	0.7184	0.545	2.58***
Forest policy on harvesting and transporting tree products to the market (dummy)	0.689	0.151	9.16***
Households' farm size	6.8131	4.318	5.42***
Household sells fuelwood (dummy)	0.737	0.696	–1.38
Log household income from selling fuelwood	2.221	2.959	–1.73**
Log of value of household assets per capita (per a.e.u)	5.651	5.461	5.17***
Pseudo-R^2	0.64		
Mean standardized bias	52.9		

Note: *, ** and *** indicate that difference between participants and non-participants is statistically significant at 10 %, 5 % and 1 % levels respectively (t-statistics test we used in mean difference).

Table 3. Difference in characteristics of the above-mentioned groups after matching.

	Mean			Reduction	t-test
	Participant	Non- participant	Bias, %	Of % bias	P-value
Sex of household head (dummy)	0.782	0.739	10.2	38.3	0.73
Household size (number)	5.043	4.173	6.9	–36.0	0.89
Education of household head (years)	5.615	4.538	1.2	93.3	0.96
Age of household head (years)	52.652	52.565	0.8	98.2	–1.19
Number of trees planted	17.174	17.739	–1.9	98.8	0.86
Household planting trees for fuelwood (yes = 1, 0)	0.615	0.347	14.7	–50.8	0.50
Forest policy on harvesting and transporting tree products to the market (dummy)	0.461	0.519	4.0	68.9	0.23
Households' farm size	5.195	4.978	6.7	91.3	0.86
Household sells fuelwood (dummy)	0.652	0.608	9.6	–6.3	0.76
Log household income from selling fuelwood	2.116	1.588	11.4	28.4	0.53
Log of value of household assets per capita (per a.e.u)	5.584	5.644	–2.8	68.6	0.34
Pseudo-R^2	0.10				
Mean standardized bias	21.3				

Note: *, ** and *** statistically significant at 10 %, 5 % and 1 % levels respectively (t-statistics test are used in mean difference).

A comparison of the results in Table 2 and Table 3 indicates that households in TPF programmes are characterized by large number of trees planted, more years of schooling and larger farms. However, after matching the mean of each covariate they did not differ significantly, suggesting fairly successful matching of the treated and control groups. As noted by Lee [23], the main purpose of the propensity score is to balance the distribution of covariates across two groups before and after matching, as shown in our findings. As for the number of trees planted variable, the difference in mean shown in the propensity score (47.563 % before matching) is reduced to 17.174 % after matching. The insignificant p-values in Table 3 suggest that the joint significance of covariates used in this study was rejected after matching. Further evidence of fairly successful matching is that the pseudo-R^2 dropped from 64 % before matching to about 10 % after matching. We also noted low mean standardized bias, and a bias of less than 20 % for all covariates, as suggested by Rosenbaum and Rubin [24].

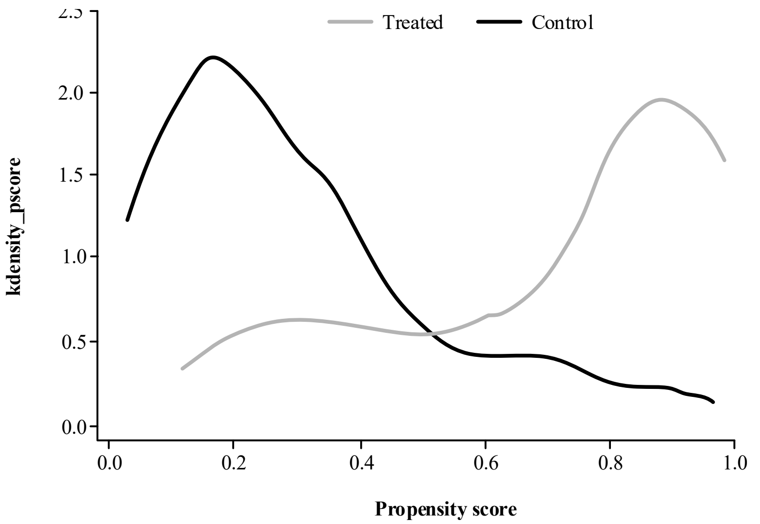

Fig. 1. Density of the propensity scores.

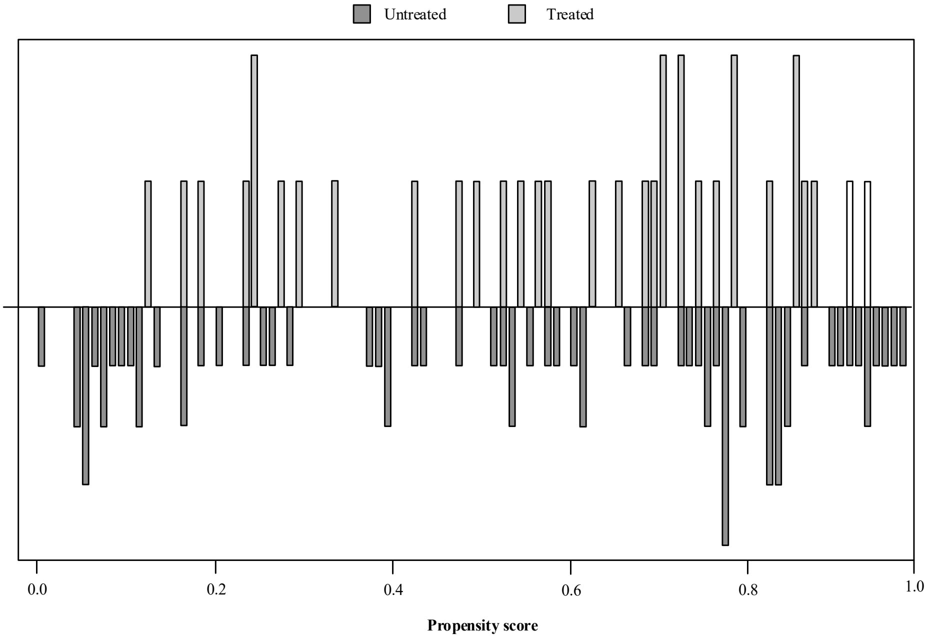

Fig. 2. Region of common support.

Furthermore, there was a substantial overlap of the matched propensity score of both groups distributed within the region of common support (Fig. 2). The results indicate that households in TPF programmes (treated) and those who are not (untreated) were within the common region, but they indicate that the percentage of TPF programme participants who planted trees for fuelwood was probably 50 % (mean; 0.51 and Dev; 0.32). We also noted that the propensity score in Fig. 1 rose in the treated group compared to their counterparts, although both distributions are skewed as they have to be from 0 to 1. We can therefore conclude that the differences in mean between participants and non-participants were eliminated via matching before engaging in TPF programmes.

Table 4. Logit Estimates of Propensity Scores of participants in TPF programmes.

Tree planting for fuelwood	Freq.	Percent	Cum
Non-participants	104	50.99	50.99
Participants	99	49.01	100.00
Total	203	100.00	
	β	Z	Standard error
Sex of household head (dummy)	0 .421	0.89	0.471
Household size (number)	–0.224	–1.41	0.159
Education of household head (years)	0.008		0.053
Age of household head (years)	0.035	1.85	0.019***
Household planting trees for fuelwood (yes = 1, 0)	1.672	2.65	0.630***
Forest policy on harvesting and transporting tree products to the market (dummy)	2.013	4.95	0.406***
Log of off-farm income	–0.113	–0.88	0.129
Households' farm size	0.145	2.16	0.067**
Household sells fuelwood (dummy)	8.272	1.36	6.075
Log household income from selling fuelwood	–1.551	–1.54	1.0095
Log of value of household assets per capita (per a.e.u)	1.7555	2.23	0.785**
Constant	–12.609	–2.73	4.626***

Despite these results, further analysis was needed to estimate the effect of covariates on the outcome variable. We employed a logit technique to estimate whether households would plant trees for fuelwood and its extent. Table 4 presents the covariates and outcome distribution (treated and non-treated) variables, which shows that out of 203 observations, 49.01 % are households in TPF programmes and 50.99 % are not. The sign (+/–) of coefficients implies that households' participation in TPF programmes was positively or negatively influenced by the respective covariate. These results indicate that TPF programmes have a positive and significant impact on the number of trees planted and those planted for fuelwood, as well as on forest policy in terms of harvesting tree products for trade, household assets, farm size, and household head's age.

As expected, households who engaged in TPF programmes were more likely to plant more trees for fuelwood. We measured average treatment effects for the treated (ATT) on propensity score matching to estimate the impact of the programmes using nearest neighbour matching (NNM), Kernel matching (KM) and radius matching (RM), which showed that TPF programmes had a significant impact on the number of tree planted by participating households.

Table 5. Impact of TPF programme on number of trees planted and trees planted for fuelwood.

Matching algorithm	Outcome variables	Treatment effects	Participant	Non- participants	Difference	Std error	T-stat
NNM	Number of trees planted	ATT	47.563	6.106	41.45	4.912	8.44***
	Trees planted for fuelwood	ATT	0.7184	0.3786	0.339	0.147	2.31**
KM	Number of trees planted	ATT	49.885	24.515	25.369	5.321	4.77***
	Trees planted for fuelwood	ATT	0.718	0.545	0.215	0.067	2.58***
Radius with Calliper 0.25	Number of trees planted	ATT	35.236	6.981	28.254	4.801	5.88***
	Trees planted for fuelwood	ATT	0.618	0.527	0.090	0.128	1.99*

The impact of TPF programmes' magnitude on covariates using NNM, KM and RM are provided in Table 5, which shows that all the matching estimator techniques produced similar outcomes after controlling for observable confounding variables, suggesting that participating in TPF programmes has a positive and statistically significant effect on the number of trees planted and planting for fuelwood in the areas studied, as non-participant households would plant 25–41 trees less. These results are similar to using Hackman's model above, which substantiates the impact of TPF programmes of switching from crop production to planting trees for fuelwood. Therefore, to understand tree-planting behaviour, fuel policy on harvesting and transporting tree products, farm size, income from selling fuelwood, household assets per capita and age of household head must be considered.

Finally, our results clearly indicate that with policies providing a clear right to harvest and transport wood products to the markets, rational households would plant trees for energy and trade. Though, the existing Tanzanian forest policies [25], including policy statement 9 and 14, target planting for fuelwood and trade only, they ignore policy issues related to the transport of tree products to the markets.

4. Conclusion

This study evaluates the impact of TPF programmes employing Hackman and PSM approaches to control for selection bias associated with censoring or truncation, and to adjust covariate distribution between programme participants and non-participants. This shows important determinants of planting trees for energy. The findings indicate that TPF programmes led to a large number of trees being planted for fuelwood in the areas studied. Our findings do not agree with those of earlier studies [26], which concluded that tree-planting programmes do not appear to cause more trees to be planted. Our results, show that a forest policy is needed to create a conducive environment for planting trees for cash in Tanzania.

We also conclude that an attempt to promote tree planting for energy should take into account the factors that affect it, such as forest policy on harvesting and transporting tree products to the market and income from selling fuelwood, which suggests that this may need a regulatory authority like EWURA.

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