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ARTICLE

The impact of agri-business skills training in Zimbabwe: an evaluation of the Training for Rural Economic Empowerment (TREE) programme

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ABSTRACT
This study presents an evaluation of the International Labour Organization (ILO) Training for Rural Economic Empowerment (TREE) programme as implemented in Zimbabwe. The programme's goal was to improve the labour market outcomes of young people in rural areas. We apply Propensity Score Matching and Difference-in-Differences methods on a two-period retrospective panel data survey (2011 and 2014) to control for biases stemming from observed and unobserved time-invariant characteristics between TREE beneficiaries and a constructed control group. We find that TREE increased beneficiaries' income by US $787, as well as child and health expenditures by US $236 and US $101, respectively, compared to non-beneficiaries over the 2011–2014 programme implementation period.

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Impact evaluation; internal rate of return; social welfare

1. Introduction

Over the years there have been several interventions in Africa that aim to reduce poverty, reinforce the agricultural sector, and generate income for people living in rural areas. Stewart et al. (2015) highlight two types of interventions that have been implemented to tackle food insecurity and poverty among smallholders in African countries: the first one focuses mainly on improving agricultural practices through training and skills development, while the second is based on familiarising and encouraging the use of new available technologies. There is some empirical evidence suggesting that combining these two types of interventions may increase agricultural production and the productivity of smallholder farmers, which in turn would increase income and agricultural employment (AGRA 2013; IFPRI 2011).

Addressing the obstacles to agricultural productivity and promoting the adoption of best farming practices, including input use and the application of available technologies, are common approaches and policy actions to alleviate poverty in rural areas in Africa, where agriculture plays a key role. In the context of smallholder farming systems, it may be especially important to focus on two key components of productivity: technological progress (e.g. use of improved inputs) and technical efficiency, which captures the ability or managerial skills of farmers to choose and use the best existing technologies (e.g. Bravo-Ureta, Greene, and Solís 2012; Triebs and Kumbhakar 2013). In sub-Saharan Africa, it has been argued that lack of skills not only undermines efficiency, but also

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limits agricultural growth. Foster and Rosenzweig (2010) make the case for the importance of education and training in assisting the acquisition and processing of new information and, by extension, the technology adoption process. Skills acquired during training can play a fundamental role in worker employability, wages and productivity (Davis et al. 2012; Piza et al. 2016). Similarly, Chun and Watanabe (2012) find that vocational skills training programmes increase income of trainees in rural areas in Bhutan in non-competitive labour markets.

Another hindrance faced by farmers in sub-Saharan Africa may be access to credit and information. The evidence suggests that credit rationing is an important constraint for farmers in developing countries in general due to such factors as high risk to lenders, lack of collateral, and asymmetric information (e.g. Conning and Udry 2007; Boucher, Carter, and Guirkinger 2008; Foster and Rosenzweig 2010). In addition, recent evidence shows that information improves farmer's knowledge, particularly regarding existing technologies, and, by extension, boosts agricultural productivity and managerial skills (e.g. Solís, Bravo-Ureta, and Quiroga 2009; Stewart et al. 2015). These types of interventions typically deliver three primary outputs: vocational skills; management and entrepreneurial skills; and financial skills, including mentoring and counselling after the intervention to ensure sustainability (Cho and Honorati 2014). Recently, the development and reinforcement of entrepreneurship skills has been the focus of several interventions in least developed countries (Gindling and Newhouse 2014).

A recent approach in development programmes in low-income countries has been the direct transfer of cash to poor and unemployed citizens to enable small business start-ups with the objective of decreasing economic disparity and promoting social stability. An example of this approach is a governmental programme in Uganda recently evaluated by Blattman, Fiala, and Martinez (2015). These authors show that giving money to low-income people in Uganda incentivises people to enrol in skill training workshops. The earnings of women who participated in the programme increased by 84% compared to women who were not part of the programme. For both men and women, the programme increased business assets and earnings by 57% and 38%, respectively. In a similar vein, Hicks et al. (2015) show that the beneficiaries of a vocational education voucher programme for out-of-school Kenyan youth obtained an additional 0.55 years of schooling while significantly increasing their hourly wage and the likelihood of obtaining a paid job compared to those who did not receive the voucher.

Several donor agencies and international organisations, including the International Labour Organization (ILO), have provided technical and financial assistance throughout Africa to encourage good employment opportunities that would translate into poverty reduction and economic growth, with a direct impact on the rural economy. For instance, the ILO, in its mission to promote and improve human and labour rights, developed the Training for Rural Economic Empowerment (TREE) programme. TREE is a community-based approach to skills development ranging from vocational and business skills to literacy and leadership training. Since 2002, TREE has been implemented in more than 20 countries and targets primarily populations that are more vulnerable in accessing quality employment, that is, people with disabilities, women and youths. The TREE approach uses a system that has three dimensions. First, at the macro level, the programme is designed to assist local economic activities by creating a policy and regulatory environment Second, at the meso level, the programme reinforces the capacity building of social partners and non-governmental organisations operating in the area. Third, at the micro level, the programme targets youth living in rural areas by providing them with training in marketable skills needed to succeed, with start-up support and post-training assistance. For example, in the Punjab of Pakistan, 93% of TREE beneficiaries secured new income and the number of women participating in the local economy increased significantly. In the Philippines, the average monthly income of TREE beneficiaries increased by 105%. As another example, in Sri Lanka, almost all TREE beneficiaries were able to find jobs and their average monthly income increased by nearly 177% (ILO 2011). It is worth noting that TREE's implementation relies on national and local communities. Therefore, the programmes take into account the local context, and implementation varies from one country to another.

This paper focuses on ILO's TREE intervention implemented in Zimbabwe, a predominantly rural country, where agriculture plays a crucial role in the economy (ZIMSTAT 2011). To support Zimbabwe's efforts to address the youth employment challenge and improve economic opportunities in rural areas, ILO adapted and implemented TREE between 2010 and 2014. The objective of TREE in Zimbabwe was to improve the integration of young people into rural labour markets, boost their incomes and enhance local development through the creation of new economic and employment opportunities. The target groups included youth in poverty, underemployed and unemployed, working in the informal economy and disabled (ILO 2011).

In this paper, we measure the impact of four sets of TREE activities (as explained in the next section) on the labour market outcomes of youth, particularly income. We use Propensity Score Matching (PSM) and Difference-in-Difference (DID) techniques to account for potential biases stemming from observable and unobservable characteristics of the studied units (TREE beneficiaries and non-beneficiaries). In addition, we go beyond the measurement and analysis of impact evaluation and examine the expected internal rate of return of the project that, despite being an indicator of importance to policy makers, it is rarely analysed (IEG 2011).

The results of our analysis suggest that the TREE programme had a positive impact on the beneficiaries. In particular, we find that young people who participated in the intervention between 2011 and 2014 report an income increase of USD $787, which we attribute to the intervention. This represents a 77% increase compared to the control group. The analysis also shows increased expenditures on children and health among TREE beneficiaries. There is no evidence of significant impacts on the consumption of food and fuel for electricity generation. A cost-effectiveness analysis, however, suggests that the positive impacts of TREE should be maintained for four additional years in order to reach a zero Net Present Value.

Due to data constraints, the paper does come with some limitations inherent to the applied retrospective evaluation design. Due to limitations in access, we were not able to utilise recent census data in the country. We were able to use some baseline data collected by the ILO before the programme began, but the bulk of our analysis relies on retrospective questions. Such questions can be biased if individuals exhibit systematic recollection errors. Similarly, the lack of a control sample created prior to programme implementation led to the creation of a control group based on data collected from non-participants at the time of our endline survey.

The paper proceeds as follows. Section 2 presents a few comments regarding Zimbabwe and the TREE Programme, including the theory of change and the logic of TREE. Section 3 lays out the methodological approach of this evaluation. Section 4 describes briefly the data and the empirical strategy. Section 5 presents the results, and Section 6 concludes the study.

2. Zimbabwe background and the TREE programme

Zimbabwe is divided into 10 provinces, which include two main cities that have provincial status for administrative purposes. According to the Poverty Income Consumption and Expenditure Survey (PICES) 2011–2012 Report of the Zimbabwe National Statistics Agency (ZIMSTAT 2011), approximately 68% of the population in the country lives in rural areas. Productivity and incomes in the agricultural sector are lower compared to other sectors in the economy. Agricultural income contributes 18% to the average annual gross income, and the sector was the second largest contributor (after manufacturing) to Gross Domestic Product (17.9%) in 2011. The average annual net cash income is estimated to be US $2,545 per household, while the Poverty and Poverty Datum Line Analysis (ZIMSTAT 2013) affirms that 62% of households are deemed poor, whilst 16.2% are in extreme poverty.[1] Poverty is most pronounced in rural areas, where 76% of the population is poor compared to 38.2% in urban areas.

The unemployment rate in Zimbabwe, which is defined as the percentage of the economically active population that is unemployed, is 7.7% (ZIMSTAT 2011). Unemployment is lower in rural areas (1.6%), though this figure hides the reality of the labour market in such areas where unpaid

family workers constitute about 22.5% of the economically active rural population, 61.6% are communal and resettlement farmers and only 11.5% are paid permanent or temporary employees or casual workers. In order to address these socio-economic issues in rural areas, a land reform and resettlement programme was undertaken by the national government in 2000 and nearly 300,000 households were settled on more than 6 million hectares. The land was taken from over 4,000 former commercial farms and reallocated in fixed quantities to farmers who owned very little or no land. Despite these efforts, the labour market is still challenging in rural areas where the labour supply is increasing.

TREE is a programme designed to integrate unemployed and vulnerable youth, aged 18 to 32, into the labour market. Between 2010 and 2014, the programme served 2,173 youth as direct beneficiaries in 19 districts. The intervention package consisted of the delivery of marketable skills and knowledge that sought to match the opportunities and comparative advantages of the targeted rural districts.[2] In addition, the programme provided follow-up and post-training support to ensure the sustainability of the outcomes. In particular, TREE in Zimbabwe contained five sets of activities: (1) set-up and capacity building; (2) skills training, technical/vocational and core work skills for youth; (3) business management training for youth; (4) post-training opportunities; and (5) training on financial literacy skills for youth. This paper focuses on the last four sets of activities. Table 1 shows in detail the results chain, different activities and underlying assumptions for TREE to provide a full picture of the intervention.

The first set of activities consisted of forging partnerships with policy makers and other stakeholders to reinforce and increase institutional capacity. Accordingly, the project's National Steering Committee (NSC), Technical Working Group (TWG) and Provincial Implementation Committee (PIC) chose the provinces and districts that participated in the programme. The choice was made based on economic needs, degree of development of each district and province, and the percentage of the youth population who met the TREE selection criteria as explained below.[3] In addition, a District Implementation Committee (DIC), composed of representatives of government ministries, microfinance institutions, youth organisations and civil society, was created to conduct surveys and identify potential markets and employment opportunities so that the programme could deliver relevant need-based training. Nine main activities were identified across the selected districts: beekeeping, horticulture, cattle fattening, potato production, green projects (such as the use of solar energy), poultry production, piggery, dairy farming, and fish farming. These activities were clustered into three groups: crop production, livestock and green jobs. The partnerships with local and national stakeholders allowed ILO to use existing government institutions and human resources to establish appropriate TREE management and governance structures.

Activity sets 2, 3, and 4 delivered vocational and core work and business skills to programme participants. Vocational and core work skills were delivered by service providers identified directly by the DIC. Business skills were delivered directly by the ILO, government trainers (trained by the ILO) and the Royal Business Consult Trust (a local, private business service provider). Through the provision of these skills, TREE intended to reinforce managerial abilities to increase technical efficiency through the adoption and use of existing and new technologies, and thereby to increase productivity and income.

The last set of activities provided financial support and literacy skills to beneficiaries in order to facilitate the start-up process of any income generating activity they decided to undertake. During the first year of TREE, beneficiaries received inputs or subsidies in the form of grants to start their individual projects. The rationale was that smallholder and young farmers do not have access to input markets or cannot afford to buy inputs. Mason et al. (2016) evaluated the impact of the National Accelerated Agricultural Inputs Access Programme (NAAIAP) on Kenyan smallholder incomes and poverty status and found that the programme had significant positive impact on maize production and poverty reduction. Filipski and Taylor (2012) report that input subsidies can be welfare efficient and improve production in Malawi and Ghana. Similarly, Smale, Birol, and Asare-Marfo (2014) found that beneficiaries of subsidies for hybrid seed in Zambia were able to increase their land and their

Table 1. Intervention's results chain and underlying assumptions.

Inputs	Activities		Outputs	Outcomes	Development Objective
(1) Budget (2) Staff (3) Local counterparts (4) Trainers (5) Partnerships (6) Facilities (7) Equipment (8) Supplies (9) Land (10) Technical expertise (11) Curricula	Set up and capacity building to national partners	(1) Engagement with key stakeholders for the introduction of the programme (2) Provision of training on the methodology. (3) Support in the implementation of feasibility studies to identify potential economic activities and training needs.	(1) TREE governance system is established at national and local levels (2) TREE model is adapted to country socio-economic context (3) Partner organisations are trained in the use of the TREE methodology (4) Youth employment challenges, sectors, and training needs are identified	(1) Increased institutional capacity of partners to identify potential market and employment opportunity areas and deliver relevant, needs-based training	Skills development increases employability of workers, the competitiveness of enterprises, and the inclusiveness of growth.
	Skills training, technical/ vocational and core work skills for youth	First, master trainers and extension workers from participating organisations trained; then, provision of skills training (theory delivered in classroom to beneficiaries, practice delivered in the field) through a competency-based curriculum. • Duration varied by sector/project	(1) Improved technical competencies (2) Improved core work skills (psychosocial skills, decision-making skills, communication and teamwork skills, and self-management, self-esteem)	(1) Increased probability of employment (2) Increase in number of hours worked (3) Reduced time to find job/shorter unemployment duration (4) Better quality of employment (contract type, duration) (5) Increased earnings (6) Increased business performance (7) Increased business investment and competitiveness (8) Additional jobs created (9) Additional businesses started	
	Business	management training for youth	Provision of management training derived from SIYB modules by ILO and selected training providers.	(1) Improved management skills (2) Improved understanding of business mechanisms (3) Improved financial literacy	

(*Continued*)

Table 1. (Continued).

Inputs	Activities		Outputs	Outcomes	Development Objective
	Post-training	opportunities analysed (credit scheme, follow-up visits)	Provision of loans to young beneficiaries deemed credit worthy by selected microfinance institutions	(1) Increased access to adequate financial services (2) Lower costs for finance (3) Higher probability of obtaining a loan, insurance or savings	
	Financial literacy skills training for youth	Provision of literacy skills by selected microfinance Institutions	(1) Improved reading and writing skills (2) Improved mathematical skills		
	Assumptions				
	(1) Target group participates in training (there is awareness about the programme's existence) (2) Correct group is targeted (e.g. participants are credit constrained) (3) Contracted training institutions conduct training		(1) Participants complete/ attend the training (2) Training addresses participants' constraints (e.g. existing skill shortages) (3) Participants learn in training/training increases skill level/ training is well matched to interests and abilities of participants (4) Training induces expected behavioural change (5) Loans are invested in the businesses	(1) Learned skills match labour market needs/demand (2) No stigmatising effects (3) Training completion and related certificate signals increased skills (4) Participants gain recognised and valued qualifications (5) Adequate economic, social, institutional and administrative conditions are in place (6) Created and supported businesses meet existing consumer demand (7) Adequate regulatory and business environment (8) Start-ups benefit from additional investment/credit/networks (9) Credit or grant is used for productive investments	

assets and display lower poverty rates. In addition, TREE attempted to promote technology adoption by providing improved seeds, assisting with the creation of green jobs to promote the use of sustainable solar technology in rural areas (e.g. solar powered irrigation system, home lighting systems) and facilitating access to credit. For the latter, ILO established a partnership with two local microfinance institutions to facilitate the provision of loans to beneficiaries.

The logic underlying the TREE intervention acknowledges the obstacles faced by farmers, and particularly the youth, in adopting best management practices that can translate into income generating opportunities. Consequently, the programme was designed to improve vocational and core skills among youth through training and extension services, promote technological improvements through the acquisition of productive assets (e.g. dairy cows, pigs, poultry, and improved seeds) and enhance managerial performance through technical assistance. The final expected outcome was more young people in productive and sustainable self-employment and thus an increase in social welfare. Poor farmers are generally known to be risk-averse, which can be a major impediment in the adoption and use of new technologies to increase production and income (e.g. Lee 1979). TREE contributes to the reduction of risk aversion by providing training and information to beneficiaries. Overall, the programme complemented governmental efforts in the promotion of youth employment and reinforced agricultural extension programmes with the intention of contributing to the improvement of living standards in rural areas.

Despite the importance of training and employment generation programmes for host countries and multilateral agencies, there is a dearth of empirical evidence regarding the impacts of such efforts in Africa (Stewart et al. 2015). Therefore, this study contributes to the empirical literature by evaluating the impact of a rural skills development programme tailored to youth on a set of social welfare indicators by contrasting the performance of beneficiaries against a carefully constructed control group. The analysis provides quantitative information that can assist international donors and policy makers in both donor and recipient countries in formulating and implementing similar interventions, with the intention of strengthening programmes and improving their outcomes.

3. Methodological approach

As stated earlier, the main objective of this study is to analyse the change in income of TREE beneficiaries that is attributable to the programme. A common parameter often used to estimate the impact of a programme is the Average Treatment Effect (ATE), which can be defined as the difference between the expected outcome with and without the programme intervention for its direct beneficiaries (Heckman, Ichimura, and Todd 1998; Bravo-Ureta et al. 2011). The problematic issue with ATE arises from the impossibility of observing simultaneously both outcomes for the same individual. Therefore, we follow the treatment effect framework suggested by Ravallion (2008), which consists of comparing the change in income of TREE beneficiaries to a counterfactual reflecting the absence of the programme that can be captured by designing a proper control group. A proper control group should be 'very' similar to the treated group (beneficiaries) at the baseline, that is, before the programme.

Specifically, we denote $P_i = 1$ for participants in TREE (T) and $P_i = 0$ for individuals in the control group (C), Y_i is the indicator of interest and X_i is a vector of covariates. Therefore, following Duflo, Glennerster, and Kremer (2007), the conditional average treatment effect on the treated (ATET) can be expressed as:

$$ATET = E\left[Y_i^T | X_i,\ P_i = 1\right] - E\left[Y_i^C | X_i,\ P_i = 1\right] = E\left[(Y_i^T - Y_i^C) | X_i,\ P_i = 1\right] \quad (1)$$

The main challenge in evaluating TREE, as is typically the case in most impact evaluation studies, is to find a robust counterfactual which enables one to identify what would have happened to the beneficiaries had they not been exposed to the TREE programme (Khandker, Koolwal, and Samad 2010).

3.1 *PSM implementation*

As is common in studies similar to this one, we use PSM techniques to identify the counterfactual, that is, the control group. We start by estimating a Logit model whose results provide the conditional probability of being a TREE beneficiary. Succinctly, the Logit equation can be written as:

$$P_i = X_i^{'}\beta + \varepsilon_i \ (2)$$

where $P_i = 1$ for participants in TREE (T) and $P_i = 0$ for individuals in the control group (C), as previously defined; and X_i is a vector of covariates that includes participant attributes that are likely to be time-invariant and unlikely to be affected by the programme. β is a vector of parameters to be estimated, and, ε_i is an error term. The results of the Logit model make it possible to calculate propensity scores and then determine the common support area (Caliendo and Kopeinig 2008).[4] The propensity scores are equivalent to the probability of being a TREE participant, considering both groups (T and C) and the set of covariates in equation 2. Alternative criteria were employed for the matching, as explained below. Subsequently, we checked if the mean values of observable attributes for treated and controls are the same after matching, which corresponds to the balancing test (Leuven and Sianesi 2015).

3.2 *Income impacts of TREE*

Once matching is done, we proceed to the impact analysis of the programme by using the DID methodology. The DID method compares the difference between the indicator under analysis for treatment and control groups prior to programme implementation versus the difference of the indicator at a point typically close to the end of the implementation of the project (year 2014 in this case). Combining DID and PSM makes it possible to address biases stemming from both observables (e.g. age, gender) and time-invariant unobservable characteristics (e.g. managerial ability, motivation) (Angrist and Pischke 2009). Using baseline and endline data sets, the DID model can be written as:

$$Y_{it} = \beta_0 + \delta P_{it} + \lambda T_t + \gamma P_{it} T_t + \beta X_{it}' + \varepsilon_{it}, \qquad i = 1, .., n; t = 1, 2 \qquad (3)$$

where the left hand side variable represents the value of the indicator of interest (i.e. income, children-related or health expenditures and consumption); P_{it} is the dummy that measures treatment status (1 if the individual is a TREE beneficiary and zero otherwise); T_t is a dummy variable equal to 0 for the baseline and 1 for the endline; γ is the treatment effect; $X_{it}'$is the transposed vector of covariates; ε_{it} is the error term; and the Greek letters are parameters to be estimated (Khandker, Koolwal, and Samad 2010).

4. Data and empirical strategy

The data for this study was collected in three steps. In the first step, we randomly selected 11 districts from the 19 where the programme had been implemented at the time of this study. This initial selection was done to facilitate logistics and to reduce data collection costs. To construct the sample frame for beneficiaries and controls, the second step consisted of matching TREE intervened wards with non-intervened wards located in the 11 districts selected. Cavatassi et al. (2011) and De los Santos and Bravo-Ureta (2017) use a similar approach.

PSM was employed to pair treated with non-treated wards based on secondary data available from ZIMSTAT. The matching consisted first of fitting a Logit model to calculate the probability of a ward being treated, where the binary dependent variable is equal to 1 for intervened wards and 0 otherwise. As shown in Table A in the Appendix Section, the variables included in the Logit model were gender, defined as the number of males and females living in the ward, number of households

Table 2. Distribution of beneficiaries and non-beneficiaries per district.

				Number of Observations		
District	Province	Number of Wards	Treated	Control	Male	Female
Chimanimani	Manicaland	18	77	228	166	139
Mutare Rural	Manicaland	19	29	39	21	47
Mutasa	Manicaland	20	36	179	109	106
Nyanga	Manicaland	17	156	293	205	244
Mt Darwin	Mashonaland	25	147	0	73	74
Murehwa	Mashonaland	3	77	0	43	34
Mutoko	Mashonaland	21	188	164	204	148
Shamva	Mashonaland	10	58	139	86	111
Nkayi	Matebeleland	10	131	177	125	183
Gokwe South	Midlands	7	114	0	72	42
Gweru Rural	Midlands	11	45	0	22	23
Total	**4**	**161**	**1058**	**1219**	**1126**	**1151**
Treated					524	534
Control					602	617

and average household size per ward, and a set of district dummies. As depicted in Table B in the Appendix, the PSM yielded 103 matched pairs of treated and control wards, a figure that includes all the intervened wards, leaving 96 unmatched intervened wards off common support. Common support is given by propensity score values that fall in the interval [0.32; 0.73]. We then randomly selected 50 of the 103 matched pairs.

The 50 intervened matched wards served as the basis to randomly choose the beneficiaries from an ILO database that contains information on several socio-demographic variables. Similar information was collected on eligible youths in the 50 matched non-intervened wards, which served as the sample frame for the control group. Subsequently, we used PSM to match individual beneficiaries with non-beneficiaries and to determine the final list of youths to be interviewed for the impact evaluation. Finally, the third step consisted of collecting the baseline and endline data needed for the evaluation.

The baseline had to be collected by applying a retrospective survey. As mentioned earlier, we were unable to access baseline data gathered prior to the implementation of the programme. Thus, data were collected for the year 2011 (baseline) and 2014 (endline) simultaneously at the end of the programme in 2014. As shown in Table 2, these data were collected in 11 districts distributed in four provinces across Zimbabwe. The final unmatched sample size includes 2,277 observations, 1,219 controls and 1,058 treated. The controls include 617 women and 602 men, while the respective gender distribution for beneficiaries is 534 women and 524 men. It is important to highlight the fact that the sample for beneficiaries clearly reveals a very low level of attrition. This low attrition can be seen from the fact that the list of beneficiaries constructed randomly from administrative data collected in 2011 had 1,058 people; of those, we were able to interview 1,007 in 2014, that is, 95.2% of those who were initially enrolled.

Table 3. Definition of variables.

Variable	Unit	Definition
BENEF	Dummy	1 if the respondent is a beneficiary of TREE
YEAR	Dummy	0 = 2011, 1 = 2014
Gender	Dummy	1 if the respondent is a female
Marital Status	Categorical	1 = Married, 2 = Single, 3 = Divorced, 4 = separated, 5 = Widowed
Vulnerability	Categorical	1 = Disabled, 2 = Ill, 3 = Able bodied, 4 = Disabled and ill
Education	Categorical	1 = None, 2 = Primary, 3 = O'level, 4 = All levels above the O'level (A'level, Certificate, Diploma and Degree)
Income	US dollars	Profits plus wages generated by respondents
Health Expenses	US dollars	Expenditures on health of the household
Children Welfare	US dollars	Expenditures on children (education, health and other expenses)
Consumption	US dollars	Expenditures on cooking items, fuel and electricity

The calculation of the sample size is based on four parameters: (1) the expected effect of TREE on income; (2) the standard deviation of the income distribution; (3) the confidence level; and (4) the statistical power (see Wassenich and Muñoz (2007) and Lachaud, Bravo-Ureta, and Fiala (2016) for more details).

A questionnaire was developed that contained information regarding demographic characteristics, family health and education, household welfare, business activities, employment, training, aspirations, risk preferences and empowerment.[5] Table 3 contains the definition of the key variables used in the impact evaluation analysis.

5. Results

As explained above, the analysis relies on PSM applied to the baseline data combined with DID using both endline and baseline data. The panel data obtained from the survey applied to TREE beneficiaries and the control group was used to estimate equation 3. First, we match beneficiaries and non-beneficiaries and then we evaluate the impact of TREE by using a DID estimator, which consists of comparing the difference in the outcome of interest of both groups at the baseline against that at the endline.

5.1 *Selection of matched beneficiaries and controls*

We start by estimating the following Logit model using baseline data in order to match beneficiaries with non-beneficiaries:

$$BENEF_i = f(Gender,\ Household\ Size, Marital\ Status,\ Education, Vulnerability) + \varepsilon_i \quad (4)$$

where all variables in equation 4 are defined in Table 3. The estimated Logit model is the basis for calculating the probability of being a TREE beneficiary. The results of the Logit model are presented in Table 4. Most of the parameters are statistically significant except the categories 2 and 4 for the variables *marital status* and *vulnerability*, respectively.

We first used the '1-to-1' nearest neighbour without replacement criterion to match beneficiaries with controls, which led to 1,004 matched pairs for a total of 2,008 observations. Next, we examined the balance property by testing the null hypothesis that the mean values of the baseline observable characteristics of treated and control individuals are equal after matching

Table 4. Logit results for participation in TREE (baseline year).

Variable	Coeff.	SD
Gender	−0.27***	0.10
Household size	0.06**	0.03
Marital1	−2.18***	0.79
Marital2	−0.70	0.66
Marital3	−1.89**	0.91
Marital4	−2.26***	0.67
Education 1	−0.01	0.38
Education 2	−1.38***	0.36
Education3	−0.60*	0.35
Vulnerability1	1.15***	0.31
Vulnerability2	1.63**	0.64
Vulnerability4	−1.45	1.10
Constant	0.79	0.77
Pseudo R2	0.136	
N	2211	
Log-Likelihood	−1316.4	

Significance level: *$P < 0.1$; **$P < 0.05$; ***$P < 0.01$

The omitted categories for Marital Status, Education, and Vulnerability are 'widowed,' 'Above O-level,' and 'Able bodied,' respectively.

Table 5. Matched and unmatched beneficiaries and controls.

Variable	Off Support	On Support	Total
CONTROL	14	1190	1204
TREATED	3	1004	1007
Total	17	2194	2211

On Support are beneficiaries/control who are within a common range of propensity scores, whereas Off support are out of that range.

(Becker and Ichino 2002). However, this test failed. Therefore, we then applied the '1-to-1' nearest neighbour with replacement criterion, which allows multiple inclusions of untreated individuals and the order of selection of the treated does not affect the matching (Austin 2014). As shown in Table 5, the '1-to-1' nearest neighbour with replacement yielded a matched dataset that includes 1,190 controls and 1,004 beneficiaries; thus, all these observations satisfy the common support condition. In this case the balancing property for the matched data holds. The results, based on student-t statistical tests conducted before and after matching, are reported in Table 6 for all observations and separately for males and females. The differences between treatment and control groups are significantly reduced. In all cases, the null hypothesis that the mean values of all the variables/categories for beneficiaries and non-beneficiaries do not differ after matching cannot be rejected at the almost 1% significance level except for the 'household size' for the females. In other words, controls and beneficiaries are similar in terms of observables at the baseline.

Before proceeding with the analysis, we also applied the Kernel criterion, which uses a weighted average of all controls to match all treated in order to check for robustness (Ravallion 2008; Almeida and Bravo-Ureta 2017). The weights are built so that they are inversely proportional to the distance between the propensity scores of treated and controls (Heckman, Ichimura, and Todd 1998). Kernel matching also leads to the acceptance of the balance condition. The analysis that follows is based on the matched 1,190 controls and 1,004 beneficiaries obtained from the '1-to-1' nearest neighbour with replacement criterion.

5.2 *Economic impact of TREE on its beneficiaries*

The matched treated and controls are then used to estimate the following equation using the DID framework:

$$Y_{it} = f(BENEF,\ YEAR,\ BENEF * YEAR,\ Gender,\ Education,\ District) + \varepsilon_{it} \quad (5)$$

where all variables are as defined before and the dependent variable, Y, is either *income, expenses on child welfare, expenses on health care or expenses on consumption* of beneficiary i, at time t (baseline or endline), and ε_{it} is the error term. The estimated parameters for the four different dependent variables (that is, TREE indicators) are presented in Table 7. The estimated income for controls at the baseline (2011), that is, the constant in the regression model, is nearly US $1,172 and approximately US $1,391 for beneficiaries ($1,172 plus the estimated parameter for BENEF $219.2).[6] In addition, the parameter for YEAR is about $320 indicating that even in the absence of the programme, the income for both groups would have increased by the latter amount during the 2011–2014 period due to other factors. Moreover, the estimated parameter for BENEF*YEAR in the income equation is $787.13, which indicates that, over the four years of the programme, income for TREE beneficiaries increased by that amount compared with non-beneficiaries.

The results also suggest substantial heterogeneity in the income distribution at baseline as shown in Table 7. For instance, it is worth noting that in 2011 women were, on average, significantly worse off than men in terms of income. In addition, the education level of participants

Table 6. Balancing t-tests performed before and after matching at the baseline for both groups.

	Sample (Panel A)	Mean			% Reduction in bias	*t*-test	
Variable		**Beneficiary**	**Control**	**% Bias**		***t***	***P > t***
Gender	Unmatched	1.00	1.00	NA	NA	NA	NA
	Matched	1.00	1.00	NA	NA	NA	NA
Household size	Unmatched	4.48	4.36	6.9		1.14	0.25
	Matched	4.48	4.24	12.8	−85.4	2.15	0.03
Marital1	Unmatched	0.01	0.02	−11.4		−1.85	0.06
	Matched	0.01	0.01	1.5	87.1	0.32	0.75
Marital2	Unmatched	0.73	0.35	82		13.56	0.00
	Matched	0.74	0.75	−3.8	95.4	−0.63	0.53
Marital3	Unmatched	0.01	0.01	−6		−0.98	0.33
	Matched	0.01	0.00	6.4	−6.4	1.73	0.09
Marital4	Unmatched	0.23	0.60	−80.6		−13.28	0.00
	Matched	0.24	0.24	−1	98.8	−0.16	0.87
Education1	Unmatched	0.12	0.05	24.5		4.12	0.00
	Matched	0.12	0.14	−9.9	59.7	−1.29	0.20
Education2	Unmatched	0.17	0.30	−30.3		−4.98	0.00
	Matched	0.17	0.16	2.5	91.8	0.44	0.66
Education3	Unmatched	0.69	0.64	10.9		1.81	0.07
	Matched	0.70	0.69	1.5	86.3	0.24	0.81
Vulnerability1	Unmatched	0.98	0.93	24.1		3.91	0.00
	Matched	0.98	0.99	−4.7	80.7	−1.20	0.23
Vulnerability2	Unmatched	0.00	0.00	−5.1		−0.82	0.41
	Matched	0.00	0.00	3.4	33	1.00	0.32
Vulnerability3	Unmatched	0.02	0.05	−16.3		−2.65	0.01
	Matched	0.02	0.01	4.3	73.6	0.99	0.32
	Sample (Panel B)						
Gender	Unmatched	0.00	0.00	NA	NA	NA	NA
	Matched	0.00	0.00	NA	NA	NA	NA
Household size	Unmatched	4.53	4.54	−0.2		−0.03	0.98
	Matched	4.54	4.52	0.6	−262.5	0.10	0.92
Marital1	Unmatched	0.01	0.01	−0.9		−0.15	0.88
	Matched	0.01	0.00	5	−461.1	1.01	0.31
Marital2	Unmatched	0.55	0.21	76.1		12.71	0.00
	Matched	0.55	0.54	2.9	96.1	0.42	0.67
Marital3	Unmatched	0.00	0.00	0.7		0.12	0.90
	Matched	0.00	0.00	4.7	−525.2	1.00	0.32
Marital4	Unmatched	0.44	0.79	−76.2		−12.70	0.00
	Matched	0.44	0.46	−4.2	94.4	−0.62	0.54
Education1	Unmatched	0.12	0.05	24.9		4.18	0.00
	Matched	0.12	0.12	−1	96	−0.13	0.89
Education2	Unmatched	0.11	0.31	−51.3		−8.35	0.00
	Matched	0.11	0.11	0.3	99.5	0.06	0.96
Education3	Unmatched	0.74	0.62	27.1		4.46	0.00
	Matched	0.74	0.74	1.2	95.7	0.19	0.85
Vulnerability1	Unmatched	0.97	0.94	13.3		2.16	0.03
	Matched	0.97	0.97	0.8	93.8	0.15	0.88
Vulnerability2	Unmatched	0.01	0.01	−0.1		−0.01	0.99
	Matched	0.01	0.02	−7.8	10,106.5	−1.06	0.29
Vulnerability3	Unmatched	0.02	0.04	−10.7		−1.75	0.08
	Matched	0.02	0.01	2.6	76	0.52	0.60
	Full Sample (Panel C)						
Gender	Unmatched	0.50	0.50	−0.4		−0.09	0.926
	Matched	0.50	0.50	1	−149.6	0.22	0.824
Household size	Unmatched	4.51	4.45	3.3		0.77	0.44
	Matched	4.51	4.39	6.4	−95.7	1.51	0.13
Marital1	Unmatched	0.01	0.02	−7.2		−1.67	0.10
	Matched	0.01	0.00	2.8	61.9	0.83	0.40
Marital2	Unmatched	0.64	0.28	77.8		18.28	0.00
	Matched	0.64	0.64	−0.2	99.7	−0.05	0.96
Marital3	Unmatched	0.00	0.01	−3.7		−0.85	0.40
	Matched	0.00	0.00	5.5	−49.1	2.00	0.05
Marital4	Unmatched	0.34	0.69	−76.6		−17.96	0.00

(*Continued*)

Table 6. (Continued).

	Sample (Panel A)	Mean			% Reduction in bias	*t*-test	
Variable		**Beneficiary**	**Control**	**% Bias**		***t***	***P > t***
	Matched	0.34	0.35	−2.8	96.4	−0.61	0.54
Education1	Unmatched	0.12	0.05	24.7		5.88	0.00
	Matched	0.12	0.13	−5.4	78.2	−1.01	0.31
Education2	Unmatched	0.14	0.30	−40.4		−9.35	0.00
	Matched	0.14	0.13	1.5	96.4	0.39	0.70
Education3	Unmatched	0.72	0.63	18.9		4.42	0.00
	Matched	0.72	0.71	1.3	93.2	0.30	0.77
Vulnerability1	Unmatched	0.97	0.94	18.8		4.33	0.00
	Matched	0.97	0.98	−1.9	89.8	−0.58	0.56
Vulnerability2	Unmatched	0.01	0.01	−1.9		−0.43	0.67
	Matched	0.01	0.01	−3.7	−97	−0.78	0.44
Vulnerability3	Unmatched	0.02	0.04	−13.7		−3.15	0.00
	Matched	0.02	0.01	3.5	74.6	1.07	0.29

Panel A and B represent the sample for females and males, respectively.
The omitted categories for Marital Status, Education, and Vulnerability are 'widowed,' 'Above O-level,' and 'Able bodied,' respectively NA: Non-Applicable

plays a role in determining the level of income. In general, 78.1% of men have a higher level of education (O-Level and above) compared to 73.6% of women. Table 7 shows that respondents with more education started the programme with an advantage compared to those who had no or a lower level, and these results are statistically significant. Furthermore, the evidence suggests that districts such as Mount Darwin, Mutare Rural and Mutasa started the programme with some advantages compared to other districts, in particular Gokwe South and Nkayi.

Similarly, during the 2011–2014 period, TREE has increased the expenses devoted to child welfare and household health of its beneficiaries by $235.9 and $101 US dollars, respectively, compared to non-beneficiaries.[7] However, there is no evidence that TREE has increased the consumption of its beneficiaries compared with non-beneficiaries. In fact, the estimated coefficient associated with consumption is negative but non-significant, suggesting that TREE beneficiaries

Table 7. Regression results for income, health and consumption: TREE beneficiaries and non-beneficiaries.

	Income		Children Welfare		Health		Consumption	
Variables	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Year	319.99***	61.58	119.01***	37.57	8.93	16.71	30.15	29.62
BENEF	219.18***	70.57	121.63***	42.47	33.54*	19.15	132.87**	33.95
BENEF*YEAR	**787.13*** **	**90.70**	**235.91*** **	**52.24**	**101.01*** **	**24.61**	**−44.79**	**43.63**
Gender	−164.25***	45.39	49.60***	25.95	−3.82	12.32	16.57	21.83
Education1	−632.50***	185.16	−254.03***	110.86	97.61*	50.24	333.33***	89.07
Education2	−998.15***	155.76	−420.38***	95.77	−25.01	42.27	−118.61	74.93
Education3	−719.51***	148.98	−301.97***	92.00	−32.05	40.43	−102.56	71.66
district1	20.28	102.74	−56.66	57.42	−207.65***	27.88	−159.90***	49.42
district2	−526.60***	134.34	−66.15	73.98	−227.49***	36.45	−211.48***	64.62
district3	−127.05	182.43	62.47	103.54	−239.39***	49.50	−205.17**	87.75
district4	832.90***	124.73	−169.63	63.82***	−132.59***	33.85	−105.97*	60.00
district5	−228.44	165.54	−292.54	85.86***	−188.27***	44.92	−154.83*	79.63
district6	177.34	157.26	−287.50	95.13***	−215.95***	42.67	−199.15***	75.65
district7	154.10	108.84	38.77	59.95	−144.92***	29.53	−143.87***	52.35
district8	−22.66	99.61	−105.63	51.66**	−144.63***	27.03	−32.79	47.92
district9	−279.22***	101.80	−145.87	57.82**	−226.66***	27.63	−162.32***	48.97
district10	−137.01	95.38	−134.85	50.31***	−203.37***	25.88	−118.18**	45.88
Constant	1171.83	173.39	782.17	102.81***	275.62***	47.05	267.03***	83.41
Adj. R^2	0.14		0.07		0.04		0.02	
N	4388		2828		4388		4388	

Significance level: *$P < 0.1$; **$P < 0.05$; ***$P < 0.01$
Different number of observations is due to missing values. The omitted category for district is Shamva (district11). The omitted category for Education is 'Above O-level.'

Table 8. Percentage change in income, health expenses and child welfare due to TREE.

Indicator	Male (%)	Female (%)
Income	46.9***	81.8***
Health	27.04***	37.3***
Children Welfare	28.15***	23.6***

Significance level: *$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.

probably devote money gained to buy assets or incur other expenses instead of consumption. When comparing treated and control groups by gender in terms of differential income, the results suggest that TREE increases the income of male and female beneficiaries by 46.9% and 81.8%, respectively, compared to their counterparts in the control group (Table 8). These results highlight the significant and positive impact of TREE on women, especially considering that they started the programme with lower income compared to men. In addition, the findings suggest that health expenditures by female beneficiaries' rose by 37.3% compared to 27.04% for men. However, male household heads who participated in the programme were able to increase expenses related to the welfare of children by 43.2% compared to 23.6% by their female counterparts.

5.3 *Internal rate of return analysis (IRR)*

Occasionally, impact evaluations go beyond the immediate impact indicator(s) and examine the net present value (NPV), the benefit-cost ratio (B/C) and/or the internal rate of return (IRR) of the project (IEG 2011). The NPV is equal to the sum of discounted inflows minus the sum of discounted outflows using a predetermined discount or interest rate. To be viable, the project must have a positive NPV, and the higher the positive value the better. The B/C represents the ratio rather than the difference of the discounted flows, and this ratio must equal 1 for the project to be economically viable and the higher the value above 1 the better. Finally, the IRR is the discount rate that yields a NPV equal to zero (Boardman et al. 2011).

This impact evaluation study focuses on four sets of activities undertaken by TREE. Recall that the average impact of TREE on beneficiaries in terms of incremental income is $787.13 for the 2011–2014 period, or an average of nearly $196.78 per year compared to non-beneficiaries. Table 9 shows the inflows of the project for the 2010–2014 period, which is the estimated benefit generated by the programme per beneficiary per year ($196.78) times the number of TREE beneficiaries in each year. This benefit amount refers to change in income only and, to avoid double counting, does not include benefits generated from health and child welfare. In other words, the extra expenses on health and child welfare come from the additional income generated by the programme. The ILO country office in Zimbabwe provided, from their administrative data, the annual cash outflows for the programme activities being evaluated in this study, which includes expenses for training and for business development after training. It is worth noting that for the year 2010, the cash outflow for business development after training was zero. The cash outflows for the four sets of activities represent 46%, 27%, 40%, and 35.2% of the total cash outflows of the programme for the years 2011, 2012, 2013, and 2014, respectively. The net cash flow is the difference between total inflows and total outflows.

Table 9 depicts the results of the analysis of the NPV, B/C and IRR. We first calculate the NPV of the project assuming a discount rate of 12%. Under this scenario (Scenario 1), given the number of beneficiaries in the programme (2173), and the total outflows associated with implementation, the NPV is negative and the ratio B/C is less than one. We then conduct a sensitivity analysis by using a discount rate equal to 6% (Scenario 2) and again find a negative NPV and a B/C ratio less than 1. That is, for the 12% and 6% discount rates, the results suggest that TREE is not profitable over the short 2010–2014 period.

Given the negative NPV generated by the programme for the 2010–2014 period, we next investigate how many years of inflows are needed for TREE to pay off. Benefits of the project in terms of additional income are assumed to continue into the future, and this could be for several

Table 9. Cash flows ($1000 US) NPV, B/C and IRR.

Scenario 1 (discount rate = 12%)					Scenario 2 (discount rate = 6%)		
Year	Outflow	Beneficiaries	Inflow	Net Cash flow	Beneficiaries	Inflow	Netflow
2010	74.39	134	26.37	(48.02)	134	26.37	(48.02)
2011	783.56	438	86.19	(697.36)	438	86.19	(697.36)
2012	270.10	873	171.79	(98.31)	873	171.79	(98.31)
2013	626.45	1664	327.45	(299.01)	1664	327.45	(299.01)
2014	461.55	2173	427.61	(33.94)	2173	427.61	(33.94)
Total	$2,216.04		$1,039.41	($1,176.64)		1,039.41	(1,176.64)
NPV				($983.43)			(1,071.34)
B/C				0.43			0.45
Scenario 3 (discount rate = 6%)					**Scenario 4**		
Year	Outflow	Beneficiaries	Inflow	Net Cash flow	Beneficiaries	Inflow	Netflow
2010	74.392	134	26.37	(48.02)	134	26.37	(48.02)
2011	783.555	438	86.19	(697.36)	438	86.19	(697.36)
2012	270.098	873	171.79	(98.31)	873	171.79	(98.31)
2013	626.452	1664	327.45	(299.01)	1664	327.45	(299.01)
2014	461.547	2173	427.61	(33.94)	2173	427.61	(33.94)
2015	0	2173	427.61	427.61	2173	427.61	427.61
2016	0	2173	427.61	427.61	2173	427.61	427.61
2017	0				2173	427.61	427.61
2018	0				2173	427.61	427.61
Total	2,216		1,894.62	(321.42)		2,749.84	533.79
NPV				(450.36)			0.00
B/C				0.77			1
IRR (%)							8.01

Beneficiaries are number of beneficiaries.

Cash inflows are the estimated benefits generated by TREE per beneficiary per year ($196.78) times the number of TREE beneficiaries in each year.

Cash outflows include expenses for the four sets of activities being evaluated: (1) skills training, technical/vocational and core work skills for youth; (2) business management training for youth; (3) post-training opportunities; and (4) financial support and literacy skills training for youth.

Cash outflows do not include fixed or sunk costs that are directly related to activity 1, 'capacity building,' which is not being evaluated.

years. We also assume in this context that there is no additional cost related to training and business development at this point, and thus the number of beneficiaries is held constant. Under Scenario 3, we add an additional two years and keep the discount rate at 6%, and the NPV is still negative. Finally, under scenario 4, and assuming four years of benefits beyond the end of the programme, we find a non-negative NPV and an IRR equal to 8%. Thus, the results suggest that the programme needs at least four additional years of benefits, for a total of eight years, to be profitable. Alternatively, for the 2010–2014 period, TREE spent a total of $2,216,044 for 2,173 beneficiaries or roughly $1,020 per person. Assuming a discount rate of 12% and 6%, the programme would need to spend no more than $ 443 or $459, respectively, to be viable, that is, to obtain a NPV equal to zero. Clearly, other scenarios could be explored to examine the sensitivity of the programme with respect to other critical variables such as the number of beneficiaries.

6. Concluding remarks

This study employs PSM along with DID to investigate the impact of the TREE programme in Zimbabwe. The application of these two approaches makes it possible to mitigate potential biases stemming from both observable and unobservable characteristics between beneficiaries and controls.

The economic analysis suggests that the TREE programme has indeed contributed to the social welfare of its beneficiaries. Specifically, over the four years (2011–2014) of implementation, TREE increased the income of its beneficiaries by US $787 compared with non-beneficiaries. Similarly, it increased child welfare and health expenditures of beneficiaries compared to controls by $236 and $101 US dollars,

respectively. There is no evidence of significant impact on consumption. Whether or not the beneficiaries devoted their income to buy other assets or other type of investments requires further analysis.

Participant's behaviour, characteristics and location can play a critical role in influencing programme outcomes. The results show that at the baseline, women were significantly worse off than men, underscoring the importance of a particular focus on young women at the onset of the programme, when beneficiaries are selected. Furthermore, the analysis of income distribution at baseline points to high heterogeneity across districts. Higher income levels in some districts may also imply better economic and employment opportunities.

The programme accomplished its objective with regard to increasing income and the child welfare and health expenditures of its beneficiaries. However, a question that remains is whether the programme targeted and selected the right people because the analysis shows that baseline average income for beneficiaries was significantly higher than for controls.

Finally, the evidence shows that, given the total cost of implementing TREE and the number of beneficiaries, four years of benefits beyond the end of the programme (with no additional cost) are needed for TREE to generate an internal rate of return (IRR) of 8%; alternatively, TREE has to reduce the cost per beneficiary by more than a half.

Notes

1. Poverty is defined as the prevalence of people in households whose consumption expenditures per capita are below the upper poverty line whereas extreme poverty refers to a shortfall below the lower poverty line (see PICES, 2011–2012 for more details).
2. From 2010 to 2014, TREE worked in 19 Districts: Beitbridge, Chegutu, Chikomba, Chipinge, Gokwe South, Gwanda, Gweru, Insiza, Makoni, Mberengwa, Mt Darwin, Murehwa, Mutare, Mutasa, Mutoko, Nkayi, Nyanga, Chimanimani, and Shamva located in the following seven Provinces: Minlands, Mashonaland East, Mashonaland Central, Manicaland, Matebeleland North, Matebeleland South and Mashonaland West.
3. The NSC is composed of, among others, Permanent Secretaries who are the chief accounting officers of government ministries, and TWG is made up of specialists and directors in government departments.
4. Common support, also known as the overlap condition, ensures that individuals with similar observable characteristics also have a similar probability of being in the programme (Caliendo and Kopeinig 2008).
5. For more details regarding the survey design and the matching at the ward level, see Lachaud, Bravo-Ureta, and Fiala (2016).
6. According to the World Bank, the Gross Domestic Product per capita of Zimbabwe in 2014 was US $1908.5 (PPP constant 2011 International US $). http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators.
7. This change in beneficiarie's income, health and children-related expenses corresponds to an increase of 73.4%, 37.8%, and 29.6%, respectively, compared to non-beneficiaries.

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Appendix

Table A. Logit estimation of propensity scores.

BENEF	Coeff.	Std. Err.
Intercept	0.31	0.95
Females	−0.0001	0.00
Males	0.0003	0.00
Number of Household	−0.35	0.25
Household size	−0.0002*	0.00
district1	0.51	0.37
district2	0.64	0.83
district3	−0.23	0.45
district4	−0.73*	0.44
district5	0.74**	0.36
district6	0.89***	0.34
district7	0.80**	0.35
district8	1.26***	0.46
district9	−0.08	0.39
Log likelihood	−164.41	
Pseudo R^2	0.15	

*10%, **5%, and ***1% level of significance. District: is a dummy variable that represents district.

Table B. Matched and unmatched wards.

Variable	Off Support	On Support	Total
Wards (Non-intervened)	96	103	199
Wards (Intervened)	0	103	103
Total	96	206	302