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

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This study presents an evaluation of the International Labour Organization (ILO) Training for Rural Economic Empowerment (TREE) program implemented in Zimbabwe to improve labour market outcomes of young people in rural areas. It applies 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. The results indicate that TREE increased beneficiaries' income by US $813 as well as child and health expenditures by US $235 and US $113, respectively compared to non-beneficiaries over the 2011-2014 program implementation period.

Keywords: Impact evaluation; internal rate of return; social welfare.

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1. Introduction

There are a number of 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 one is based on familiarizing and encouraging the use of new available technologies. There is empirical evidence suggesting that combining these two types of interventions may increase agricultural production and 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 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 programs increase income of trainees in rural areas in Buthan in non-competitive labour markets.

Other hindrances faced by farmers in this region 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 various factors such 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 farmers’ knowledge, particularly as regards to existing technologies and by extension boosting agricultural productivity and managerial skills (e.g., Solis, Bravo-Ureta and Quiroga, 2009; Stewart et al. 2015).

Several donor agencies and international organizations, including the International Labour Organization (ILO), have provided technical and financial assistance throughout Africa to encourage decent employment opportunities that would translate into poverty reduction and economic growth, with a direct impact on the rural economy. This paper focuses on an ILO 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, the ILO designed a youth employment and skills development intervention, implemented between 2010 and 2014. The rural component of the intervention focused on the application of the ILO's Training for Rural Economic Empowerment (TREE) program TREE's objective 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 youth, youth working in the informal economy, and disabled youth (ILO, 2013).

The objective of this paper is to measure the impact components 2 and 3 of TREE (as explained in the next section) on labour market outcomes of youth, particularly income. We use Propensity Score Matching and Difference-in-Difference 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 program had a positive impact on the beneficiaries. In particular, we find that young people who benefitted from the intervention between 2011 and 2014, report an income increase of USD $813 attributable to the intervention, which represents a 77% increase with respect 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 (Gertler et al. 2011). We were able to use some baseline data collected by the ILO before the program 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 program 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 Program 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.

2. Zimbabwe background and the TREE program

Zimbabwe is divided into 10 provinces that 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.

According to ZIMSTAT (2011), the unemployment rate in Zimbabwe, which is defined as the percentage of the economically active population that is unemployed, is 7.7%. 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

[1] Poverty is 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).

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 program was undertaken by the national government in 2000 and nearly 300,000 households were settled on more than 6 million hectares (ZIMSTAT, 2011). The land was taken from over 4,000 former commercial farms and reallocated in fixed quantities some assistance to farmers who owned very little or no land. Despite these efforts, the labour market is still challenging in rural areas where labour supply is increasing.

TREE is a program designed to integrate unemployed and vulnerable youth, aged 18 to 32 into the labour market. Between 2010 and 2014, the program served 2,173 youth as direct beneficiaries. The intervention package consisted in 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 program provided follow-up and post-training support to ensure the sustainability of the outcomes. Table 1 shows in detail the intervention's results chain and underlying assumptions.

[Table 1]

TREE contained three main components. The first component consisted of engaging 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 program. The choice was made based on economic needs, degree of development of each district and province, and the percentage of the youth population who complied with the TREE selection criteria as explained below.[3] In addition, a District Implementation Committee (DIC), constituted of government ministries, microfinance institutions, youth organizations and civil society, was created to conduct surveys and identify potential markets and employment opportunities so that the program could deliver relevant need-based training. Nine main activities were identified across the selected districts: beekeeping,

[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 constituted, among others, of Permanent Secretaries who are the Chief Accounting Officers of Government Ministries and TWG is made up of Specialists and Directors in Government Departments.

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.

The second component delivered vocational, core work, and business skills to program 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 the use of existing and new technologies, and thus to increase productivity and income.

The third component provided financial support 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 as a grant to start their individual projects. The rationale for this component 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 Program (NAAIAP) on Kenyan smallholder incomes and poverty status and find that the program 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) find that beneficiaries of subsidies for hybrid seed in Zambia were able to increase their land, their assets and display lower poverty rates. In addition, the 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 program 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 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 needed to increase production and income (e.g., Lee, 2005). TREE contributes to the reduction of risk aversion by providing training and information to beneficiaries. Overall, the program complemented governmental efforts in the promotion of youth employment and reinforced agricultural extension programs with the intention of contributing to the improvement of living standard in rural areas.

Despite the importance of training and employment generation programs 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 program 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 programs and improving their outcomes.

3. Methodological approach

As stated earlier, the main objective of this study is to analyze the change in income of TREE beneficiaries that is attributable to the program. A common parameter that is often used to estimate the impact of a program is the Average Treatment Effect (ATE), which can be defined as the difference between the expected outcome with and without the program 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 states of 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 against a counterfactual reflecting the absence of the program 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, i.e., before the program.

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, the conditional average treatment effect on the treated (ATET) can be expressed as (Duflo, Glennerster and Kremer, 2007):

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

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 program (Khandker, Koolwal and Samad, 2010).

3.1 Propensity score matching (PSM) implementation

As is common in studies similar to this, we use Propensity Score Matching (PSM) techniques to identify the counterfactual, i.e., 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:

$$P_i = X_i'\beta + \varepsilon_i \quad (2)$$

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 program; 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. Given the nature of the data, as explained below, the matched sample is constructed using the Kernel algorithm criterion that uses a weighted average of all controls to match all treated. The weights

[4] Common support also known as the overlap condition ensures that youths with similar characteristics (e.g., covariates) have a positive probability of being beneficiaries or non-beneficiaries.

are built so that they are inversely proportional to the distance between the propensity scores of treated and controls (Heckman et al. 1998). Subsequently, we check if the mean values of observable attributes 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 program by using the Difference-in-Difference (DID) methodology. The DID method compares the difference between the indicator under analysis for treatment and control groups prior the program 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:

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

where the left hand side variable represents the value of the indicator of interest (i.e.., income, children related or health expenses, 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 et al., 2010).

4. Data and empirical strategy

The data for this study was collected in three steps. The first step was to randomly select districts. Eleven were chosen randomly, out of a total of 19 where the program was implemented. This selection was done to facilitate logistics and to reduce data collection costs. The second step consisted of matching TREE intervened with non-intervened wards located in the 11 selected districts in order to construct the sample frame for beneficiaries and controls. For the matching we used PSM using secondary data available from ZIMSTAT. The PSM analysis yielded 50 matched pairs of non-intervened and intervened wards. The 50 intervened matched wards served as the sample frame to randomly choose the beneficiaries from an ILO database that contains information on several socio-demographic variables. Similar information was collected on eligible but non-beneficiary youths (individual level) 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 impact evaluation.

[Table 2]

The baseline had to be collected by applying a retrospective survey, as mentioned earlier, because no such data had been gathered prior to the implementation of the program. Thus, data were collected for the year 2011 (baseline) and 2014 (endline) simultaneously at the end of the program in 2014. As shown in Table 2, 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. The calculation of the sample size is based on four parameters: i) the expected effect of TREE on income; ii) the standard deviation of the income distribution; iii) the confidence level; and iv) the statistical power (see Wassenich, 2007; Lachaud, Bravo-Ureta and Fiala, 2016 for more details).

[Table 3]

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 Propensity Score Matching (PSM) applied to the baseline data combined with Difference-in-Difference (DID) using both endline and baseline data. The panel data obtained from the survey applied to TREE beneficiaries and the control

[5] For more details regarding the survey design and the matching at the ward level, see Lachaud et al. (2016).

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

First, we start by estimating the following Logit model using baseline data for beneficiaries and non-beneficiaries[6]:

$$BENEF_{it} = f(Gender, Household\ size, Marital\ Status, Vulnerability\ status, Income) + \varepsilon_{it} \quad (4)$$

where all the 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 3 for the variables *marital* and *vulnerability status*, respectively.

[Table 4]

We first used the 1-to-1" nearest neighbour without replacement criterion to match beneficiaries with controls, which led to 1,007 matched pairs for a total of 2,014 observations. However, the key variables in equation 4, except for vulnerability status, did not balance. Therefore, we changed the matching criterion and used the Kernel algorithm that has the advantage of using all the available data (Heckman et al. 1998).

[Table 5]

As shown in Table 5, the Kernel Matching leads to a matched dataset that includes a total of 1,192 controls and 1,007 beneficiaries, and all of which satisfy the common support condition. Next, we examine whether the values of the observable characteristics of both groups are, on average, equal for the baseline data after matching. This is the so-called balancing property mentioned briefly previously (Becker and Ichino, 2002). The results of the Balancing test, based on student-t statistical tests conducted before and after matching are reported in Table 6. In all cases, the null hypothesis that the mean values of the variables for beneficiaries and non-beneficiaries do not differ-after matching cannot be rejected at the 1% significance level. In other

[6] Other variables were considered when estimating the models, but their inclusion leads to the failure of the balancing property.

words, after the kernel matching the balancing property holds, i.e., controls and beneficiaries are similar in terms of observables at the baseline. Thus, the analysis that follows is based on the matched 1,192 controls and 1,007 beneficiaries.

[Table 6]

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 children welfare*, *expenses on health care or expenses on consumption*, and ε_{it} is the error term. The estimated parameters for the four different dependent variables (i.e., TREE indicators) are presented in Table 6. The estimated income for controls at the baseline (2011), which corresponds to the constant in the regression model, is nearly US $600.3 and US $ 832.8 for treated ($600.3 plus the estimated parameter for BENEF $232.5).[7] In addition, the estimated parameter for YEAR is $320.4 indicating that even in the absence of the program, income for both groups would have increased by US $320.4 during the 2011-2014 period due to other factors. Moreover, for the income equation, the estimated parameter for BENEF*YEAR is $813.2, which indicates that the income of TREE beneficiaries increased by that amount with respect to non-beneficiaries over the four years of the Program.

[Table 7]

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 plays a role in determining the level of income. When looking at the estimated parameters for education in Table 7 ("No education" is the omitted dummy variable), the findings show that respondents with primary education, or an "O' level", started the program

[7] According to the World Bank, the Gross Domestic Product per capita of Zimbabwe in 2011 is US $677 (constant 2005 US $). http://data.worldbank.org/data-catalog/world-development-indicators.

with a disadvantage compared to those who had an "A level" (obtained a certificate). The estimated parameters associated with those who had a diploma or a degree are not statistically significant. This latter result can be explained by the fact that only one respondent reported having a diploma or a degree in the sample. Furthermore, the evidence suggests that districts such as Mount Darwin, Mutare Rural and Mutasa started the program with some comparative advantages compared to other districts, in particular Gokwe South and Nkayi.

[Table 8]

Similarly, during the 2011-2014 period, TREE has increased the expenses devoted to Children Welfare and Household Health of its beneficiaries by $234.7 and $112.9 US dollars, respectively, compared to non-beneficiaries.[8] However, there is no evidence that TREE has increased the Consumption of its beneficiaries with respect to non-beneficiaries. In fact, the estimated coefficient associated with consumption is negative but non-significant suggesting that TREE beneficiaries probably devote money gained to buy assets or incur other expenses instead of consumption. When comparing treated and controls by gender in terms of differential income, the results suggest that TREE increases the income of male and female beneficiaries by 37% and 54.7%, respectively, compared to their counterparts in the control group (Table 8).

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. The project to be viable 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 the training and business development components of the program. Recall that the average impact of TREE on beneficiaries in terms of

[8] This change in beneficiaries' income, health and children related expenses to an increase of 77%, 31.2% and 38.9% compared to non-beneficiaries, respectively.

incremental income is $819 for the 2011-2014 period or an average of $204.8 per year compared to non-beneficiaries. Table 8 shows the inflows of the project for the 2010-2014 period, which is the estimated benefit generated by the program per beneficiary per year ($203.3) times the number of TREE beneficiaries in each year. The ILO country office in Zimbabwe provided from their administrative data the annual outflows of the Program components being evaluated in this study. The netflow is the difference between the inflows and outflows.

[Table 9]

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 program (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 program 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 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 we keep the discount rate at 6% and the NPV is still negative. Finally, under scenario 4 with a discount rate again of 6%, and assuming four years of benefits beyond the end of the program we find a non-negative NPV and an IRR equal to 9.3%. Thus, the results suggest that the program needs at least four additional years of benefits, for a total of eight years, to pay off. Clearly other alternatives could be explored to examine the sensitivity of the Program such as the number of beneficiaries.

6. Concluding remarks

This study employs propensity score matching (PSM) along with difference-in-difference (DID) to investigate the impact of the Training for Rural Economic Empowerment (TREE) program 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 program 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 $813.2 with respect to non-beneficiaries. Similarly, it increased children welfare and health expenses of beneficiaries compared to controls by $234.7 and $112.9 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 program outcomes. The results show that at the baseline, women were significantly worse off than men; emphasizing the importance of a particular focus towards young women at the onset of the program, 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 program accomplished its objective as regards to increasing income, children welfare and health expenses of its beneficiaries. However, a question that remains is whether the program 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 program (with no additional cost) are needed for TREE to generate an internal rate of return (IRR) of 9.3%.

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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 program 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 socioeconomic context 3. Partner organizations 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. o Duration varied by sector/project	4. Improved technical competencies 5. Improved core work skills (psychosocial skills, decision-making skills, communication and teamwork skills, and self-management, self-esteem)	2. Increased probability of employment 3. Increase in number of hours worked 4. Reduced time to find job/shorter unemployment duration 5. Better quality of employment (contract type, duration) 6. Increased earnings 7. Increased business performance 8. Increased business investment and competitiveness 9. Additional jobs created 10. Additional businesses started	
	Business management training for youth	Provision of management training derived from SIYB modules by ILO and selected training providers.	6. Improved management skills 7. Improved understanding of business mechanisms 8. Improved financial literacy		
	Post-training opportunities analysed (credit scheme, follow-up visits)	Provision of loans to young beneficiaries deemed credit worthy by selected microfinance institutions	9. Increased access to adequate financial services 10. Lower costs for finance 11. Higher probability of obtaining a loan, insurance or savings		
	Financial literacy skills training for youth	Provision of literacy skills by selected microfinance Institutions	12. Improved reading and writing skills 13. Improved mathematical skills		

Assumptions				
	1. Target group participates in training (there is awareness about the program'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 stigmatizing effects 3. Training completion and related certificate signals increased skills 4. Participants gain recognized 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	

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

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
Marital Status	Categorical	1= Married, 2= Single, 3=Divorced, 4= separated
Vulnerability	Categorical	1= Disabled, 2= Ill, 3= Able bodied, 4=Disabled and ill, 5=Other
Education	Categorical	1= None, 2= Primary, 3= O'level, 4= A level, 5= Certificate, 6= Diploma, and 7= Degree
Income	US dollars	Sum of profit and wages generated by respondents
Health Expenses	US dollars	Amount of money spent on health for the household
Children Welfare	US dollars	Amount of money spent for children (education, health and other expenses)
Consumption	US dollars	Amount of money spent on cooking items, fuel and electricity

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

Variable	Coeff.	SD
Gender	-0.274***	0.09
Household size	0.058**	0.025
Income	0.003**	0.000
Marital1	-2.032***	0.755
Marital2	-0.662	0.624
Marital3	-1.968**	0.874
Marital4	-2.233***	0.626
Vulnerability1	0.975***	0.300
Vulnerability2	1.078*	0.645
Vulnerability3	-1.49	1.086
Constant	0.28	0.65
Pseudo R2	0.1	
N	2211	
Log-Likelihood	-1337.2	

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

Table 5: Matched and Unmatched Beneficiaries and Controls

Variable	Off Support	On Support	Total
CONTROL	12	1192	1204
TREATED	0	1007	1007
Total	12	2199	2211

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

Variable	Sample	Mean Beneficiary	Control	% Bias	% Reduction in bias	t-test T	P>t
Gender	Unmatched	0.50	0.50	0.5		-0.09	0.92
	Matched	0.50	0.48	-3.4	-639.1	0.66	0.50
Household size	Unmatched	4.50	4.44	3.3		0.77	0.44
	Matched	4.49	4.46	1.5	2.3	-0.71	0.47
Income	Unmatched	47.7	20.9	2.1		8.17	0
	Matched	47.7	43.6	5.2	84.8	1	0.32
Marital1	Unmatched	0.007	0.01	-7.2		-1.67	0.09
	Matched	0.007	0.008	-0.6	99.8	-0.17	0.87
Marital2	Unmatched	0.64	0.28	77.8		18.28	0.00
	Matched	0.64	0.64	-0.1	99.8	-0.03	0.97
Marital3	Unmatched	0.004	0.006	-3.7		-0.85	0.40
	Matched	0.004	0.004	0.3	91.6	0.08	0.94
Marital4	Unmatched	0.34	0.69	-76.6		-17	0.00
	Matched	0.34	0.34	-1	98.7	-0.23	0.82
Vulnerability1	Unmatched	0.97	0.93	18.8		4.33	0.00
	Matched	0.97	0.97	1.9	90.1	0.52	0.6
Vulnerability2	Unmatched	0.005	0.007	-1.9		-0.43	0.66
	Matched	0.005	0.005	0.3	97.7	0.06	0.95
Vulnerability3	Unmatched	0.00	0.01	-15.7		-3.55	0.00
	Matched	0.00	0.00	0.4	97.7	0.25	0.80
		P>chi2	MeanBias	MedBias			
Sample	Unmatched	0	22.8	7.5			
	Matched	0.646	1.1	0.5			

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

	Income		Children Welfare		Health		Consumption	
Variables	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD
Year	320.3***	62	127.8***	37.9	5.6	16.8	27.3	29.5
BENEF	232.5***	71.3	123.8***	42.9	34.2*	19.3	133.4***	33.9
BENEF*YEAR	**813.2*** **	91.6	**234.7*** **	52.8	**112.9*** **	24.8	**-39.9**	43.6
Gender	-151.2***	45.8	53.4***	26.2	-4.7	12.4	16	21.8
educ1	-354.6***	122.8	-174.7***	69.3	-118.3***	33.3	-447.1***	58.5
educ2	-58.8***	115.7	-56.1***	65.2	-123.5***	31.4	-430.1***	55.1
educ3	491.7	203.4	313.6	123.4	-66.8	55.2	-344.1***	96.8
educ4	1516.6**	381.2	246.4**	208.5	-179.8*	103.5	-180.5	181.5
educ5	760.8***	681.4	-716.2	489.3	-85.6	185	-437.5	324.5
educ6	-169.7	759.1	-520.1	689	-200.6	206.1	-537.2	361.5
district1	-76.1	102	-81.8	57.3	-211.8***	27.7	-155.3***	48.6
district2	-627.4***	134.9	-88.5	74.5	-234.2***	36.6	-208.7***	64.3
district3	-246.3	183.1	34.3	104.1	-249***	49.7	-203.2**	87.2
district4	707.9***	124.4	-200.2***	63.7	-141.1***	33.8	-104.4*	59.3
district5	-332.7**	165.9	-279.1***	86.1	-197.6***	45.1	-151.1*	79.1
district6	43.3	155.2	-315.7***	96.3	-225.4***	42.1	-202.9***	73.9
district7	53.7	108.4	13.12	59.9	-149.8***	29.4	-139.6***	51.6
district8	-137.1	98.6	-129**	51.2	-147.6***	26.8	-27.6	47.1
district9	-376.1***	100.9	-175.7***	57.5	-233.1***	27.4	-157.7***	48.1
district10	-233.2***	94.4	-162.6***	49.9	-207.5***	25.6	-113.3**	45
Constant	600.3***	134.5	554.9***	74.6	372.6***	36.5	591.6***	64.1
Adj. R^2	0.15		0.08		0.04		0.02	
N	4396		2828		4392		4392	

Note: Significance level: *, P<0.1; **, P<0.05; ***, P<0.01

Different number of observations is due to missing values

Table 8: Percentage change in Income, Health expenses and Children welfare due to TREE

Indicator	Male (%)	Female (%)
Income	37.0***	54.7***
Health	21.5*	21.4*
Children Welfare	69.5***	17.3***

Note: Significance level: *, P<0.1;**, P<0.05; ***, P<0.01

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	Netflow	Beneficiaries	Inflow	Netflow
2010	74.4	134	27.2	(47.1)	134	27.2	(47.1)
2011	783.5	438	89	(694.5)	438	89	(694.5)
2012	270.1	873	177.5	(92.6)	873	177.4	(92.6)
2013	626.4	1664	338.3	(288.2)	1664	338.3	(288.2)
2014	461.5	2173	441.7	(19.7)	2173	441.7	(19.7)
Total	$2,216		$1,073.8	(1,142.2)		$1,073.8	(1,142.2)
NPV				(958.7)			(1,042.4)
B/C				0.45			0.46

Scenario 3 (discount rate =6%)					Scenario 4 (discount rate =6%)		
Year	Outflow	Beneficiaries	Inflow	Netflow	Beneficiaries	Inflow	Netflow
2010	74.4	134	27.2	(47.1)	134	27.2	(47.1)
2011	783.5	438	89	(694.5)	438	89	(694.5)
2012	270.1	873	177.5	(92.6)	873	177.5	(92.6)
2013	626.4	1664	338.3	(288.2)	1664	338.3	(288.2)
2014	461.5	2173	441.7	(19.7)	2173	441.7	(19.7)
2015	0	2173	441.7	441.7	2173	441.7	441.7
2016	0	2173	441.7	441.7	2173	441.7	441.7
2017	0	2173	441.7		2173	441.7	441.7
2018	0	2173	441.7		2173	441.7	441.7
Total	$2,216	2,173	$1,971.3	(258.67)	2173	$2,840.9	$645.1
NPV				(400.83)			0.00
B/C				0.79			1.00
TIR (%)							9.3

Note: Beneficiaries are number of beneficiaries