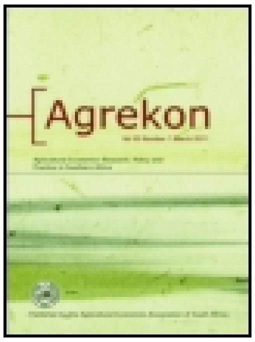

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Impact of smallholder farmers' welfare through participation in on-farm regional projects in East Africa

Enock Warinda[a], Dickson M. Nyariki[b], Stephen Wambua[c] and Reuben Muasya[d]

[a]Association for Strengthening Agricultural Research in Eastern and Central Africa, Entebbe, Uganda; [b]School of Business and Economics, Murang'a University of Technology, Murang'a, Kenya; [c]Department of Agricultural Economics & Agribusiness, South Eastern Kenya University, Kitui, Kenya; [d]Department of Dryland Agriculture, South Eastern Kenya University, Kitui, Kenya

ABSTRACT
This paper uses panel data from 1,160 smallholder farmers, especially participants and non-participants in twenty-three regional projects from five countries in East Africa – Burundi, Kenya, Rwanda, Tanzania and Uganda. In this paper, regional projects mean projects implemented jointly in at least three countries, thereby providing sustainable regional public goods. Propensity score matching analysis is used to determine the difference in net benefits accrued to the on-farm participants compared to non-participants. The propensity scores show that participants have overall higher crop and livestock productivity, enhanced household income, increased soil and water management, and access to biofortified foods compared to non-participants. These findings indicate that regional projects can catalyse the achievement of smallholder farmers' food and nutrition security, besides enhancing achievements of the African Union Commission's Comprehensive Africa Agriculture Development Programme (CAADP) and Sustainable Development Goals (SDGs).

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On-farm regional projects; household welfare; East Africa; propensity score matching

1. Introduction

Africa has the fastest growing population in the world, projected to increase from 1.1 billion in 2015–2.5 billion people by 2050 (Nieves et al. 2017). This growth in population is expected to have huge implications on natural resources, agriculture, future food security, investments and public policy. In a bid to address this growth, the United Nations though its Sustainable Development Goals seek to, among other goals end poverty (SDG1) as well as end hunger, achieve food security and improved nutrition, and promote sustainable agriculture (SDG2). Interventions aimed to boost agricultural productivity and double agricultural production and incomes of small-scale producers through secure and equal access to land, inputs, technology, markets and non-farm employment and cooperation in investments in infrastructure (HLPE 2015; UN 2016; Hanjra et al. 2017) can be fast tracked through encouraging the smallholder farmers to engage in on-farm activities undertaken at regional level.

Literature review shows that the impacts of regional projects on smallholder productivity and income have rarely been examined in empirical studies (World Bank 2008; Lynum et al. 2016; Ochieng et al. 2016), yet enhanced on-farm activities have been shown to significantly contribute to higher crop and livestock productivity, increased household income, improved soil and water management, increased resilience, and access to biofortified foods (Shin, Kim, and Sohn 2017; Shikuku

CONTACT Enock Warinda enock.warinda4@gmail.com Association for Strengthening Agricultural Research in Eastern and Central Africa, Plot 5 Mpigi Rd., P.O. Box 765, Entebbe, Uganda

et al. 2017; Asfaw et al. 2012; Hisali, Birungi, and Buyinza 2011; Kristjanson et al. 2012; Tittonell et al. 2010), especially if carried out at regional scale. Unfortunately, most smallholder farmers are unwilling to invest in recommended agricultural productivity-enhancing technologies due to uncertainty on returns on their investments (Cooper et al. 2008; Ochieng et al. 2019).

Panel data is taken from 1,160 smallholder households including participants (61%) and non-participants (39%) with gender disaggregated data including women (40%) from two spells in 2012 and 2017. Instead of a singular commodity or country focus, the projects and innovations examine target priority food commodities impacting multiple countries across the Eastern and Central Africa sub-region. These commodities include: quality protein maize (QPM), beans, mosaic resistant cassava and sorghum, quality seed potato (OFSP), banana value chain, and milk production, given their importance to livelihoods and food security of millions across the region. The difference-in-differences (DiD) method coupled with the propensity score matching are applied to address potential sample selection bias characteristic in similar studies involving participants and non-participants with common pre-treatment attributes (Rosebaum and Rubin 1983).

The rest of the paper is organised as follows: the next section presents a literature review. Section three discusses the methodology used in collecting and analysing the data, while sections four and five discuss the empirical findings and the conclusion and recommendations, respectively.

2. Literature review

Regional on-farm projects refer to multi-country or trans-boundary interventions carried out on the farms by smallholder farmers. They refer to similar activities with wider scope intended to tackle challenges affecting multiple countries across nation-state boundaries such as limitations in agriculture technology, human capacity, cross border biosafety (especially sanitary and phytosanitary measures), market access, agriculture policy and response to climate change (Ferede, Ayenew, and Hanjra 2013; World Bank 2008; Shin, Kim, and Sohn 2017; Orenstein and Shach-Pinsley 2017; Rockström et al. 2016).

Studies on the impact of regional projects on participants engaged in on-farm sector reveal assorted benefits and synergies. Participants, as opposed to non-participants have benefited from strengthened partnerships (Orenstein and Shach-Pinsley 2017; Shin, Kim, and Sohn 2017); increased soil fertility through nitrogen fixing legumes (Xia et al. 2017; Mungai et al. 2016); enhanced on-farm intensification and productivity (Rockström et al. 2016; Ahlerup, Baskaran, and Bigsten 2017); timely availability of information on new crops and markets for their produce; access to new varieties (Shikuku et al. 2017; Tittonell et al. 2010; Paul et al. 2017); and enhanced capacity on good agronomic practices and disease and pest management.

On the other hand, regional (as opposed to national) livestock integration offers higher returns to smallholder farmers especially for participants in on-farm regional projects. According to Notenbaert et al. (2017), introducing legumes into existing pasture in smallholder systems with high yielding grass improves cow diets and milk production. Data from Lushoto district in northern Tanzania where 16 village-level innovation platforms were established shows significant welfare impacts on producers and market agents. These impacts are in form of increased incomes and employment in dairy production, improved milk processing and marketing, enhanced legume productivity per hectare, reduced soil loss and improved soil nitrogen balance (Mottet et al. 2017; Lal 1987; Mungai et al. 2016). The participants in regional projects adopted new dairy, rice, cassava and wheat technologies imported from Kenya, Tanzania, Uganda and Ethiopia, respectively. Similarly, data from 884 households engaged in on-farm activities across Rwanda shows that improved livestock feed varieties imported from Kenya and Uganda benefitted nearly 40% of the households and is the most promising option to achieve triple win outcomes of food security, adaptation, emissions (Paul et al. 2017).

This paper is informed by the lack of studies on estimation of the impact of cross-regional projects on smallholder farmers' livelihoods. For instance, the launch of the African Union's Comprehensive

Africa Agriculture Development Programme (CAADP) in 2003 and the approval of the CAADP Results Framework in 2014, with an investment target of 10% of national expenditure on agriculture was expected to promote implementation of cross-regional projects, resulting in regional public goods. Unfortunately, minimal progress has been noted at the national and regional level (AUC 2018). It is noteworthy that the Malabo Declaration on Accelerated Africa Agricultural Growth and Transformation (A3GT) 2025 that specifies seven commitments aimed at achieving agricultural transformation for sustainable growth and shared prosperity from national projects and hardly on implementation of cross-regional projects. Similarly, in as much as the Science, Technology and Innovations Strategy for Africa (STISA) 2024 that focuses on allocating 1% of gross domestic product towards research and development was set up to contribute to cross-regional project implementation, its implementation has been slow. Fortunately, the Africa Union Agenda 2063 and the African Development Bank's Feed Africa Strategy 2025 (AfDB 2016) that are being implemented to address food and nutrition security issues across Africa (Williams 2015, 2017) rides on the design and implementation of cross-regional projects. However, to ensure sustainable benefits, effective implementation of these strategies requires a well-coordinated and collaborative regional, as opposed to national on-farm development projects that also bring in multiple countries and stakeholders.

3. Methodology

3.1 Source of data

The data used in this study are obtained from two spells of a survey of 1,260 farmers randomly selected from 42 villages located in the five countries of East Africa. In each village, 30 smallholder farmers are randomly drawn for the face-to-face interviews. Using a pre-tested questionnaire, two survey rounds were conducted to collect two sets of panel data between June and September of 2012 (Panel 1), and June and September of 2017 (Panel 2). Out of the targeted respondents, 92% (representing 1,160 respondents) completed the survey, comprising 61% participants and 39% non-participants in the regional projects.

3.2 Data analysis method

The DiD method, coupled with the propensity score matching approach (Mendola 2007; Gitonga et al. 2013; D'Agostino 1998; Weitzen, Lapane, and Toledano 2004; Westreich, Lessler, and Funk, 2010), is applied to assess the net effect of smallholder farmers' welfare through participation in on-farm activities supported by the regional projects. These methods are widely used to minimise selection bias with individual level panel data in impact evaluation studies (Abadie 2005; Donald and Lang 2007). The non-parametric propensity score matching method is used as a robustness check and comparison in DiD to estimate the effects of the treatment, which here refers to participation in the on-farm activities implemented under regional projects as well as to reduce bias in effect estimates (Stuart 2010; Stuart et al. 2014).

As a robustness check for DiD estimates, we use a three-step approach to conduct propensity score matching, namely: (i) we define the matching covariates and estimate the propensity scores for the whole sample as well as the resultant sub-samples; (ii) we match the estimated propensity score using a simple 1:1 nearest neighbour matching (NNM) where treated respondents are paired with control units which have the closest propensity scores. We apply the calliper of 0.15 of the standard deviation of the logit of the propensity score to include unmatched respondents as recommended by Thoemmes (2012); and (iii) we calculate the average treatment effect on the treated with a DiD estimator because it mimics unobserved heterogeneity that mostly leads to selection bias (Heckman et al. 1998).

In this paper, we define propensity score, $e(x)$ as the conditional probability of assigning the respondent to the regional projects (treatment), given a vector of observed covariates (Rosebaum and Rubin 1993; Imbens and Wooldridge 2009). We express this as:

$$e(x_i) = p(z_i = 1|x_i), \tag{1}$$

where x_i are variables which predict participation in regional projects (treatment, $z_i = 1$). Among the covariates of interest used in the analysis include sex, age, type of farmer, marital status, level of education, household size, land owned, membership in other participatory farmer groups, earnings from farming, crop and livestock production, value productivity per hectare, as well as access to agricultural technologies and innovations.

From this Equation (1), we assume that:

$$p(z_1, \ldots, z_n|x_1, \ldots, x_n) = \prod_{i=1}^{N} e(x_i)^{z_i}\{1 - e(x_i)\}^{1-z_i}. \tag{2}$$

We then estimate the propensity score using the following logistic regression:

$$e(x) = p(z = 1|x) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n}, \tag{3}$$

where $x_1, x_2, \ldots x_n$ are individual covariates; $\beta_0, \beta_1, \ldots \beta_n$ are the corresponding regression coefficients, with coefficient β_0 representing the influence of absolute component (value of probability when all covariates are equal to zero). The parameters β_0, β_1 to β_n are estimated from the data using the maximum likelihood method. We use the generated propensity score to create a pseudo-randomised dataset, thus allowing an unbiased estimator of the treatment effect (Littnerova et al. 2013).

Given that our parameter of interest is the average treatment effect of regional projects on on-farm activities (ATT_j), we therefore calculate this parameter as the mean difference in outcome across these two groups as follows:

$$\boldsymbol{ATT_j} = \boldsymbol{E}[\boldsymbol{I}_{1j}|\boldsymbol{RP_j} = 1] - \boldsymbol{E}[\boldsymbol{I}_{0j}|\boldsymbol{RP_j} = 0], \tag{4}$$

where ATT_j = Impacts of the regional projects measured as the average treatment effect of the treated for each project; I_{1j} = Value of the outcome of farm household (or other participating entity) after participation in the programme; I_{0j} = Value of the outcome of the same farm household j if he/she had not participated in the project (or participated in a similar national project); RP_j = Regional projects, where 1 indicates participation, and 0 otherwise.

3.3 Impact evaluation approach

In this paper, the DiD estimator is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the comparison group before and after treatment, thus becoming a good counterfactual for the treatment group (Heckman et al. 1998; Abadie 2005). The impact of the regional projects is hereby estimated as:

$$Y_{it} = \alpha + \delta T_{i1} t + \pi T_{i1} + \gamma t + \epsilon_{it}, \tag{5}$$

where Y_{it} = farmer's benefits (in terms of income, yield or productivity) accrued from engagement in the projects (farmer i at time t); T_{i1} = engagement in intervention ($T = 1$ if farmer engages in intervention, e.g. adoption of new technologies, and $T = 0$ if otherwise); t = survey round ($t = 0$ for panel 1 in 2012; $t = 1$ for panel 2 in 2017); δ = impact of intervention (double difference), representing interactions between post-project engagements (T_{i1}) and time ($t = 1, \ldots, n$ years); and ε = the error term.

In this method, we present a two-period setting, whereby $T = 0$ is regarded as the status of the respondents before the project (panel 1: year 2012), and $T = 1$ regarded as their status after the project implementation (panel 2: year 2017). Letting Y_t^P and Y_t^{NP} represent the respective impacts to the regional project participants and the non-participants in time t, we use the DiD method to estimate the benefits/impact of the project to the participants as:

$$DiD = E\{Y_1^P - Y_0^P | T_1 = 1\} - E\{\{Y_1^{NP} - Y_0^{NP} | T_1 = 0\}. \quad (6)$$

4. Results and discussion

After performing matching of participants in on-farm regional projects and non-participants to ensure that the respondents with similar covariates have equal propensities of participating in the regional projects, significant differences between the two groups was observed. Using an independent *t*-test and logistic regression based on propensity score matching, we calculate the DiD ($\hat{\phi}_{DiD}$) using the framework shown in Table 1.

Based on Equation (5), direct logistic regression is performed on selected covariates assumed to influence change in farm incomes among the respondents. The model with all the covariates is statistically significant (χ^2 (7, $N = 941$) = 888.31, $p < 0.001$), indicating that it can be applied to distinguish between the respondents with increased and decreased farm incomes, disaggregated by engagement in regional projects. The model explains between 53.5% (Cox and Snell *R*-square) and 85.5% (Nagelkerke *R*-squared) of the variance in increased farm incomes. It also correctly classifies 96.9% of the cases. Following regression iterations, twelve covariates generated unique statistically significant contribution to the model (Table 2). Based on the recorded odds ratios for selected covariates, it is evident that the participants who hire farm labourers, own land and keep livestock have higher probability of increased farm incomes compared to non-participants (controlling for all other factors in the model).

In running the propensity score matching, 424 treatment cases are matched with 424 control cases (out of the 1,160 respondents). From the control group, 16 respondents are unmatched, compared to 260 for treated farmers. None of the samples is outside the common support. The output shows that the overall Chi-square balance test is not significant (χ^2 (11) = 17.37, $p = .097$), thus suggesting that matching has helped reduce the bias associated with observable characteristics. Similarly, the larger multivariate imbalance measure ($L_1 = .980$) before matching compared to $L_1 = .971$ after matching indicates that matching improves the overall balance. The univariate balance test also shows that the standardised mean differences for all covariates are balanced at $|d| \leq 0.25$. Figure 1 shows the propensity scores based on farm incomes for matched respondents

Table 1. Framework for calculating difference-in-differences (DiD).

	Pre (2012)	Post (2017)	Post–pre difference (2017–2012) = ($\hat{\phi}_1$)
Participants in regional projects (treatment) in 2012 ($t = 0$) and 2017 ($t = 1$)	Y_0^P	Y_1^P	$Y_1^P - Y_0^P$
Non-participants in regional projects (control) in 2012 ($t = 0$) and 2017 ($t = 1$)	Y_0^{NP}	Y_1^{NP}	$Y_1^{NP} - Y_0^{NP}$
Difference between Treatment & Control (P – NP, $\hat{\phi}_2$)	$Y_0^P - Y_0^{NP}$	$Y_1^P - Y_1^{NP}$	$(Y_1^P - Y_1^{NP}) - (Y_0^P - Y_0^{NP})$ ($\hat{\phi}_{DID}$)

Table 2. Logistic regression predicting increase in farm incomes.

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Variables	6.2	1.432	18.8	1	.000	494	29.89	8179.13
Sex of the respondents	−.58	.371	2.4	1	.121	.562	.272	1.16
Years of education of the respondents	−.11	.042	7.0	1	.008	.894	.823	.97
Whether respondent hires labourers	7.86	.651	145.4	1	.000	2,578	718.96	9242.13
Respondent's land size (Ha)	2.01	.297	45.7	1	.000	7.463	4.17	13.37
Land size under new technology (Ha)	−2.05	.364	31.9	1	.000	.128	.063	.26
Whether respondent owns livestock	.42	.072	34.6	1	.000	1.527	1.33	1.76
Constant	−11.10	1.224	82.3	1	.000	.000		

Source: Authors, based on survey data (2018).

per country. The distribution of propensity scores of pooled samples shown in Figure 2 indicates some overlaps in the treatment and control groups. The paper shows that the standardised mean differences before and after matching generated from NNM and kernel matching algorithm method are slightly skewed from zero, indicating higher propensity scores among the groups (Table 3). The standardised mean differences for all covariates before and after matching also show a significant improvement of scores after matching is observable compared to before matching (Table 4). The mean bias of 2.6 measures the average of the differences between treatment and control group on all covariates. It indicates that the treatment and control groups became much more balanced than the unmatched sample, thus showing a good match.

4.1 Dynamics of on-farm income from regional projects

Household income from on-farm activities varies among the countries, the farmers, and over time. On average, the participants generate at least US$223 above their non-participant counterparts (Table 5). Smallholder farmers in Uganda record the highest average income gains of US$372 per household because of adoption of assorted technologies, innovations and management practices from other countries. Increases in on-farm income generated by participants from on-farm activities in

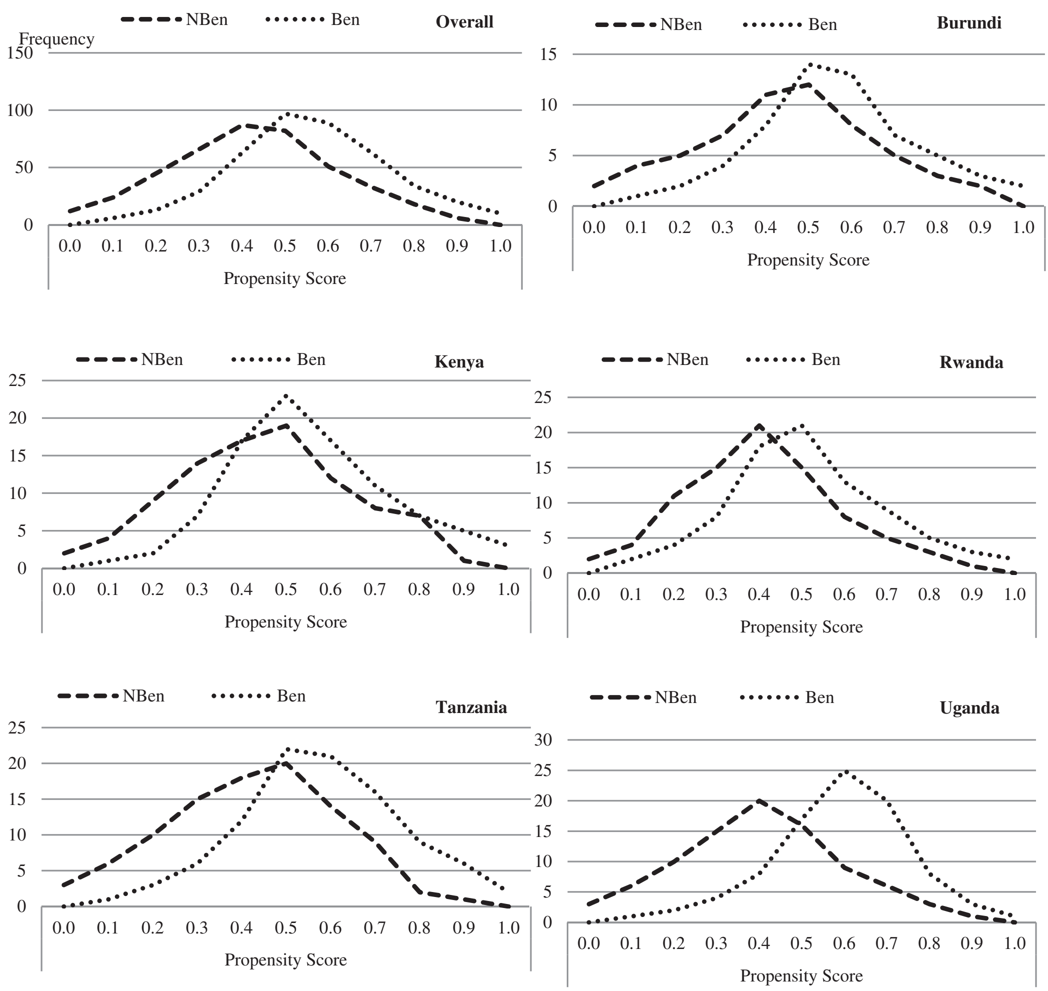

Figure 1. Propensity scores based on farm incomes for matched respondents (overall and per country).

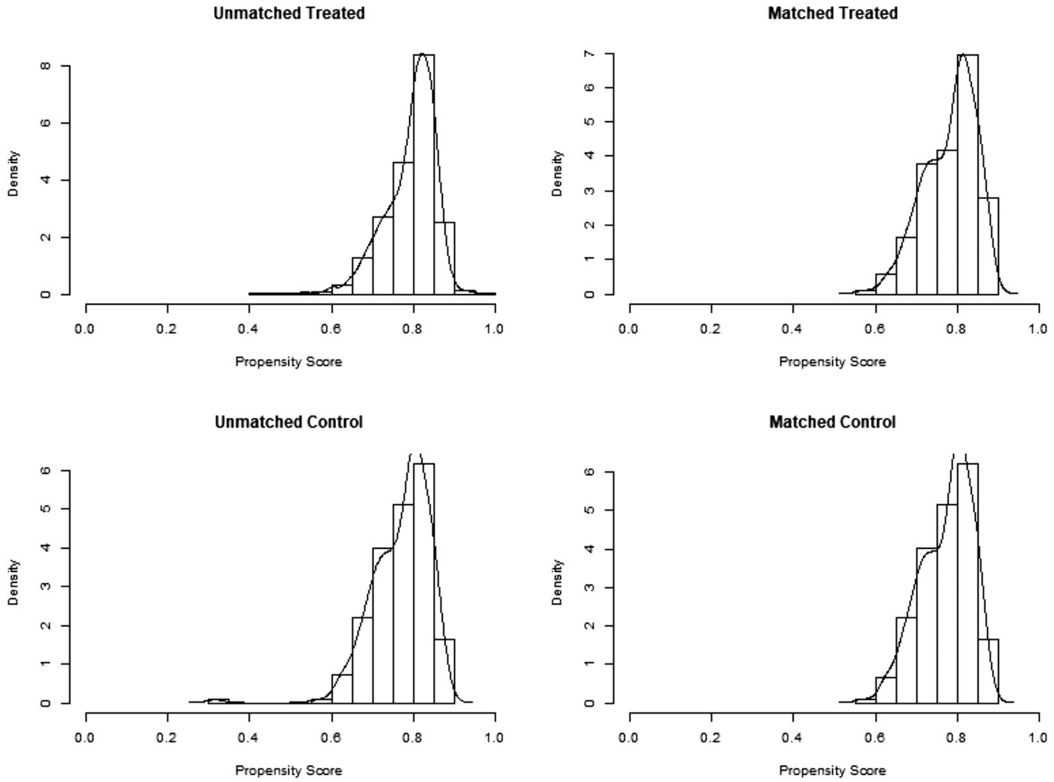

Figure 2. Distribution of pooled sample propensity scores.
Source: Based on survey data (2018).

Table 3. Matching quality indicators before and after matching for participation.

Matching algorithm method	Pseudo-R^2 before matching	Pseudo-R^2 after matching	P > Chi Square before matching	P > Chi Square after matching	Mean standardised bias before matching	Mean standardised bias after matching
NNM	0.089	0.017	45.86 (0.00)	38.54 (0.119)	5.09	2.67
Kernel	0.089	0.015	45.86 (0.00)	23.74 (0.132)	5.09	2.59

Source: Own calculation.

Burundi (US$206) are notable (Table 6). In as much as this country has experienced fragility, the implementation of regional projects, exhibited by adoption of regionally shared technologies has made the participants better off than their non-participant counterparts. The participants generate at least US$206 per household more than non-participants through the adoption of technologies availed by the regional projects. The significant increase in on-farm income by the participants in Uganda (US$372), Burundi (US$206), and Tanzania (US$205) is explained by the existence of enhanced advocacy, community-based awareness campaigns as well as reliable extension programmes for scaling up available technologies. These activities give the participants an opportunity to access new technologies, assorted trainings (on good agronomic practices, crop and livestock management, pest and disease control, and value addition) as well as access to credit facilities (from the banks, micro-credit institutions, government credit schemes as well as informal savings and credit groups) earlier not available to them, especially cassava, banana and sorghum technologies.

Table 4. Standardised mean differences (Cohen's d) for all covariates before and after matching.

	Before matching			After matching		
Variables	Treated	Control	% Bias	Treated	Control	% Bias
A1	0.467	0.451	5.8	0.467	0.636	−4.7
B1	0.533	0.512	3.2	0.533	0.521	11.7
B4	42.569	43.598	−9.4	42.569	41.300	17.9
B7	8.138	5.289	22.1	8.138	8.448	−15.5
B20	0.429	0.378	16.3	0.429	0.436	−12.4
C1	0.733	0.610	19.5	0.733	0.731	12.6
D53	0.554	0.476	9.5	0.554	0.530	15.8
E3	3.040	3.132	−4.5	3.040	3.042	−9.3
E11	1.425	1.540	−6.9	1.425	1.446	−17.4
E16	0.525	0.540	−11.7	0.525	0.514	17.4
G1	597.631	687.837	−12.9	597.631	593.273	11.6
Mean bias			5.1			2.6
Median bias			4.3			3.2
Pseudo R^2			0.189			0.017
Multivariate imbalance measure			0.980			0.971

Source: Own calculation.

Notes: A1 = type of respondent (participant/non-participant); B1 = respondent's gender (male/female); B4 = respondent's age (years); B7 = respondent's level of education (years); B20 = whether respondent hires labourers (Yes/No); C1 = whether respondent is a member of a farmer organisation (Yes/No); D53 = whether respondent has access to credit facilities (Yes/No); E3 = respondent's land size (ha); E11 = whether respondent has land dedicated to new technologies (Yes/No); E16 = type of farming practiced by respondent (monocropping or mixed cropping); G1 = level of crop productivity (kg/ha).

Table 5. Average country DiD in farm incomes (by gender) and TLU.

	Average country level DiD in farm incomes (US$/household/year)	Average value productivity/ha	Average DiD of TLU for participants	Average post-pre difference in farm income (US$/household/year) by gender	
				Male	Female
Burundi	206	815	6.99	162	270
Kenya	174	1,578	1.42	210	106
Rwanda	174	1,264	1.64	249	82
Tanzania	205	1,498	1.03	162	257
Uganda	372	1,085	0.87	374	371
Overall	223	1,248	2.14	218	226

Source: Own calculation.

4.1.1 Gender and income dynamics

Contrary to the observations by (Itabari et al. 2011; Cooper et al. 2008, 2009), that most smallholder farmers are unwilling to invest in recommended agricultural productivity-enhancing technologies due to uncertainty on returns on their investments, smallholder farmers engaged in regional projects have demonstrated positive returns on their investments by an extra US$223 above non-participants.

A significant difference in the amount of incomes generated by both male and female participants engaged in on-farm activities is observable (Table 7). Overall, the female participants record an average of US$226 (compared to male, US$218) above the non-participants. In as much as the female participants in Burundi and Tanzania generate US$108 and US$95, respectively from farming above the male participants, they are still better off than the non-participants by the

Table 6. Average post-pre differences in farm incomes at household level (US$/household/year) between respondents.

	Burundi		Kenya		Rwanda		Tanzania		Uganda	
Year	P	NP	P	NP	P	NP	P	NP	P	NP
2017	587	374	954	783	1,096	906	895	689	988	615
2012	393	386	770	773	782	766	528	527	531	530
Change	**194**	**−12**	**184**	**10**	**314**	**140**	**367**	**162**	**457**	**86**

Note: P = Participants; NP = Non-participants
Source: Own calculation.

same amount. Even though male dominance in income generation is observable in Kenya and Rwanda (with average income gap of US$104 and US$167 respectively, between male and female), the female participants are still better off than their non-participant counterparts by US $106 and US$82, respectively. The generally high average income among the female participants is attributed to their increased access to credit facilities (33.3%) and training opportunities (27.6%), adoption of availed technologies such as QPM (31.7%) and OFSP (29.8%), thereby enhancing availability of Vitamin A for their families, active engagement in farmer organisations (35.5%) as well as hiring of more human labourers (33.8%) to meet their increasing farm demands (Table 5). The findings confirm the fact that farming forms the preferred occupation by women within the rural areas where women supply up to 50% of farm labour in the five countries (Christiaensen 2017) and grow the bulk of staple foods.

To ensure more stable on-farm incomes, some of the women have signed contracts with private sector companies. Compared to the male participants (Table 5), Uganda records the highest DiD income (US$371) generated by female participants above the non-participants, followed by Burundi (US$270), Tanzania (US$257), Kenya (US$106), and Rwanda (US$82). The main source of farm incomes includes cultivation of maize, beans, sweet potatoes, cassava and bananas, as well as actively engaging in women groups, attending field demonstrations and national trade fairs, and participating in assorted trainings on good agricultural practices, soil and water management and marketing. Other studies show 20–25% gender gap in agricultural productivity in Africa (Christiaensen 2017; Doss et al. 2017). Therefore, our findings on higher female DiD provide important reasons for further investments in raising female productivity in agriculture. Activities like women empowerment are likely to contribute to closing the yield gap and improving nutritional outcomes of children.

4.1.2 Dynamics of value productivity for selected crops

Increased value productivity contributes to agricultural transformation among the smallholder farmers. We determine value productivity per hectare for each crop using farmer estimates and records on yields, harvest prices and land area under each commodity. Harvest prices used are the prevailing market and farm-gate prices, such that:

$$C_j = \left(\frac{\sum_{i=1}^{N} [A_i * Y_i * P_i]}{\sum^{i=1} A_i} \right), \tag{7}$$

where, C_j = value productivity per ha for each crop; A_i = area under the i^{th} crop (ha); Y_i = yield per ha of the i^{th} crop (metric tons); and P_i = farm harvest price of the i^{th} crop.

Results show that value productivity per hectare varies significantly within the countries and commodities (Table 8), probably due to high dependence of respondents on rainfed agriculture, access to water for livestock and supplemental irrigation, differences in agro-ecological zones, weather-related

Table 7. Average post-pre differences in on-farm incomes between male and female respondents (US$/household/year).

	Burundi		Kenya		Rwanda		Tanzania		Uganda	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
P – 2017	565	623	929	1,006	1,119	1,075	846	960	1,007	973
P – 2012	406	372	716	885	782	796	492	577	541	523
Δ	159	251	213	121	337	279	354	383	466	450
NP – 2017	487	292	767	795	854	963	746	622	629	600
NP – 2012	490	311	764	780	766	766	554	496	537	521
Δ	−3	−19	3	15	88	196	192	126	91	79
DiD	**162**	**270**	**210**	**106**	**249**	**83**	**162**	**257**	**375**	**371**

Source: Own calculation.

Notes: P – 2012, P – 2017 = Participants' average farm incomes in 2012 and 2017. NP – 2012, NP – 2017 = Non-participants' average farm incomes in 2012 and 2017. **Δ** = Post-pre differences in farm incomes between male and female respondents. DiD = Observed double difference between respondents.

Table 8. Value productivity per hectare for food commodities (US$/ha/year).

		Maize		Sorghum		Millet		Beans		Sweet potato		Cassava		Banana		Irish potato		**TOTAL**			
		2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	**Post-pre**	**DiD**
Ken	P	216	552	275	529	145	417	219	534	245	568	369	754	215	564	125	335	1,809	4,253	**2,444**	***1,578***
	NP	210	381	277	313	140	365	220	248	248	366	372	395	212	387	120	210	1,799	2,665	**866**	
Rwa	P	140	380	190	354	159	339	178	337	125	279	222	751	166	489	80	177	1,260	3,106	**1,846**	***1,264***
	NP	146	210	192	228	163	224	176	262	124	201	230	332	161	302	84	99	1,276	1,858	**582**	
Tan	P	343	623	306	530	92	414	87	602	120	325	207	579	137	410	75	163	1,367	3,646	**2,279**	***1,498***
	NP	350	542	210	255	95	120	86	382	122	176	210	283	140	198	72	110	1,285	2,864	**781**	
Uga	P	146	398	120	299	230	461	57	251	125	332	222	461	110	350	140	312	1,150	2,864	**1,714**	***1,085***
	NP	151	208	122	154	233	364	55	100	120	239	219	313	106	203	143	197	1,149	1,778	**629**	
Bur	P	95	198	141	295	37	274	45	312	441	642	80	188	69	153	59	127	967	2,189	**1,222**	***815***
	NP	93	151	140	194	35	101	43	123	438	490	78	122	71	88	62	98	960	1,367	**407**	
Total P		940	2,151	1,032	2,007	663	1,905	586	2,036	1,056	2,146	1,100	2,733	697	1,966	479	1,114	6,553	16,058	**9,505**	***1,248***
Total NP		950	1,492	941	1,144	666	1,174	580	1,115	1,052	1,472	1,109	1,445	690	1,178	481	714	6,469	9,734	**3,265**	
P–NP		**−10**	**659**	**91**	**863**	**−3**	**731**	**6**	**921**	**4**	**674**	**−9**	**1,288**	**7**	**788**	**−2**	**400**	**84**	**6,324**	**6,240**	
DiD		***134***		***154***		***147***		***183***		***134***		***259***		***156***		***80***		***1,248***			

Source: Survey data (2018).

Note: Ken = Kenya; Rwa = Rwanda; Tan = Tanzania; Uga = Uganda; Bur = Burundi; P = Participants; NP = Non-Participants.

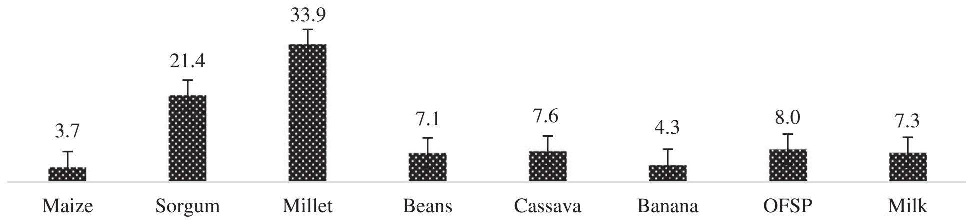

Figure 3. Average total commodity consumption by participants.
Source: Based on survey data (2018).

changes as well as emergence of pests and diseases. We also observe that some of the participants' farms have improved such that the previously weak-structured soils are no longer susceptible to degradation and drought stress. Similarly, some of the participants experience greater increases in value productivity compared to non-participants by an average of US$1,248 annually per country. Given variations in levels of adoption of availed technologies and access to credit facilities, training opportunities and market information, Kenya records the highest annual value productivity per hectare (US$1,578), while Burundi has the lowest (US$815). The results further show significant variations in the average value productivity per hectare for each of the priority commodities (Table 5).

Notwithstanding the farmers' fear of re-emergence of cassava mosaic disease in Uganda, Tanzania, Kenya and Rwanda, the commodity's annual value productivity is ranked highest (US$259 per ha), while the annual value productivity per hectare for beans, banana, sorghum and millet are US$183, US$156, US$154 and US$147, respectively. The figures indicate greater potential in enhancing value productivity of these priority commodities within the region. In as much as significant increases above the non-participants' further illustrate the impact of regional agricultural development projects, policy makers need to explore new approaches for increasing value productivity of potatoes (sweet and Irish), given that majority of smallholder farming households need this commodity as sources of Vitamins A, B & C in their diets.

4.1.3 Dynamics of average tropical livestock units between participants

The paper shows that engagement in regional projects increases average Tropical Livestock Units (TLU) among the participants. We assume that one (1) TLU comprises 0.63 bulls, 0.09 goats, 0.09 sheep, 0.18 pigs and 0.01 poultry. Each of the participants from the five countries contributes an average of 2.39 TLU compared to non-participants. Participants in Burundi, Rwanda and Kenya contribute nearly 7, 1.6 and 1.4 times more TLU to the total regional TLU than non-participants, respectively (Table 5). Participants in Burundi record the highest TLU than other countries. This is because the participants of the cross-regional projects in the country accessed new technologies that helped improve their stocking levels following the great losses in herds experienced during the civil war. In Uganda, each of the participants contributes only 0.87 times more TLU than non-participants because majority of the participants in Uganda are more focused on crop production than livestock rearing, since the projects were implemented in crop-dominated zones.

4.1.4 Average commodity consumption by respondents

Participation in regional projects enables the participating smallholder farming households to increase the production of all commodities, thereby leading to a growth in average annual consumption by 11.3 times above the non-participating counterparts. This further enables these participants to diversify their diets by exchanging some of the surplus commodities with those not produced on-farm. The most commonly consumed commodities within all the countries are millet and sorghum, with participants consuming up to 33.9 and 21.4 times more than the national averages / non-participants (Figure 3). The huge amount of daily millet and sorghum consumed is accounted for by the fact that majority of the participants are capable of affording up to three meals daily, as opposed to non-participants who access an average of two meals daily.

5. Conclusion and recommendations

The study shows that regional agricultural projects generate several benefits that are categorised into economic benefits to farmers, capacity strengthening benefits to farmers and other stakeholders, and public benefits in agriculture policy environment. The economic benefits to the smallholder farmer participants include gains in crop yield, livestock productivity, on-farm, and food security outcomes. Based on the finding, the following are the big picture messages and implications for policy makers: (i) invest in regional agricultural systems to enhance food security and support transformational change through adoption and scaling up of improved technologies and innovations. New benefit-sharing approaches should be adopted such as smart subsidies and tax credits on farm inputs and equipment like irrigation pumps and improved livestock breeds; (ii) invest in local and region-wide partnerships and capacity strengthening initiatives including investments in trainings on on-farm sustainable land and water management; (iii) create an enabling policy environment that ensures cross-border trade and exchange of crop and livestock breeds; and (iv) facilitate partnerships between farmer organisations, civil society groups, research institutes, private companies and policy networks.

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