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Chepchirchir R[1,2], Macharia I[2] , Murage A.W[3], Midega C.A.O[1]., Khan Z. R[1]

[1]International Centre of Insect Physiology and Ecology (*icipe*), P.O. Box, 30772- 00100, Nairobi, Kenya
[2]Kenyatta University, Department of Agribusiness Management and Trade, P.O. Box 43844, 00100 Nairobi, Kenya

[3]Kenya Agricultural and Livestock Research Organization (KALRO), P.O BOX 25-20117, Naivasha, Kenya

Abstract

The paper evaluates the impact of adoption of push-pull technology (PPT) on household welfare in terms of productivity, incomes and poverty status measured through per capita food consumption in eastern Uganda. Cross sectional survey data was collected from 560 households in four districts in the region: Busia, Tororo, Bugiri and Pallisa, in November and December 2014. Tobit model was used to determine the intensity of adoption of the technology whereas generalized propensity scores (GPS) was applied to estimate the dose-response function (DRF) relating intensity of adoption and household welfare. Results revealed that with increased intensity of PPT adoption, probability of being poor declines through increased yield, incomes, and per capita food consumption. With an increase in the area allocated to PPT from 0.025 to 1 acre, average maize yield increases from 27 kgs to 1,400 kgs, average household income increases from 135 USD (UGX 370,000) to 273 USD (UGX 750,000) and per capita food consumption increases from 15 USD (UGX 40,000) to 27 USD (UGX 75,000). The average probability of being poor declines from 48% to 28%: This implies that increased investment on PPT dissemination and expansion is essential for poverty reduction among smallholder farmers.

Key words: Push-pull technology, generalized propensity score, household welfare, Uganda

Introduction

Agricultural productivity is one of the key determinants of agricultural growth (Salami, 2010). Progress towards food and nutritional security requires that food is available, accessible and of sufficient quantity and quality (Mellor, 1999; FAO, 2012). Although increase in agricultural productivity is a necessary condition for progress in poverty and hunger reduction, it is not sufficient especially in the face of rapidly growing human population. Hence inclusive agricultural growth that promotes equitable access to food, assets and resources, especially for poor and vulnerable people is key. This is particularly so in the developing world where majority of the poor and hungry people live in rural areas, and where family farming and smallholder agriculture is a prevailing mode of farm organization (FAO, 2012; Kosura, 2013). Growth in family farming and smallholder agriculture through labour and land productivity increases has significant positive effects on the livelihoods of the poor through increases in food availability and incomes (FAO, 2015).

Cereal crops, including maize (*Zea mays* L.), sorghum (*Sorghumbicolor* (L.) Moench), and rice (*Oryza sativa* L.*)* are the most important food and cash crops for millions of rural farm families in sub-Saharan Africa (SSA) who predominantly practice mixed crop-livestock farming systems under diverse climatic and ecological conditions (Romney et al., 2003; Kosura, 2013). Despite the importance of cereal crops in the region, yields on smallholder farms are often very low, attributable to negative abiotic and biotic constraints faced by the farmers (Smil, 2000). Stemborer pests, striga weeds, and low soil fertility have been ranked as some of the most important constraints to efficient production of cereal crops by smallholder farmers in SSA. Indeed, maize yield losses caused by stemborers can reach as high as 80% in some areas whereas losses attributed to striga weeds can range between 30 and 100%, and are often aggravated by low soil fertility. With high prevalence of both pests occurring simultaneously, farmers often lose their entire crop (Musselman et al., 1991; Kim 1991; Khan et al., 1997). These losses, which amount to approximately USD 14 billion annually in SSA, have mostly affected the resource poor subsistence farmers resulting into high levels of food insecurity, malnutrition and poverty (Hassan et al., 1994; Kfir et al., 2002; Khan et al., 2014; *icipe*, 2015).

Although Uganda has always been considered self-sufficient in food production at the national level and a net exporter of food to neighboring countries, many households and specific segments of the population suffer from food insecurity and high levels of malnutrition (Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) (MAAIF, 2004). Cereal production in the country is affected by a number of constraints, including the ones above (Bahiigwa, 1999, 2004; Ssewanyana and Kasirye, 2010; Mukhebi et al., 2011; Turyahabwe et al., 2013). In response to the challenges posed by the production constraints above in SSA, the International Centre of Insect Physiology and Ecology (*icipe*) in collaboration with other partners developed a habitat management strategy, termed 'push-pull' technology (PPT)[1], for integrated management of stemborers, striga weeds and poor soil fertility. Farmers practicing this technology have increased their maize and fodder yields, improved milk production and realized improvement in soil fertility (Khan et al., 2008a; Midega et al., 2015).. To date, this technology has been adopted by over 110,000 smallholder farmers in eastern Africa.

[1] PPT involves intercropping cereal crops (in this study maize) and desmodium (e.g. *Desmodium uncinatum*), with Napier grass (*Pennisetum purpureum* Schumach) or Brachiaria grass (*Brachiaria cv mulato II*) planted as a border crop around this intercrop (Khan et al., 2001, 2004; Midega et al., 2010). The desmodium repels stemborer moths ('push'), while the surrounding grass attracts them ('pull') (Khan et al., 2001). In addition, desmodium suppresses *Striga* weeds through a number of mechanisms, with allelopathy (root to root interference) being the most important in this case (Khan et al., 2008b; Midega et al. 2010).

While a lot of literature has been documented on PPT in the previous studies, very little has been documented on its impact on household welfare, including poverty reduction and improvements in incomes. Most of the previous studies considered the perception of the technology based on the principles of the beneficiary assessment approach (Fischler, 2010). The current study deviates from this approach and evaluates the empirical questions of whether the intensity of adoption of the technology has improved the welfare of the farmers.

Analytical framework

Several studies have assessed the impact of technology adoption simply by examining the differences in mean outcomes of adopters and non-adopters, or by either using simple regression procedures that include the adoption status variables among the set of independent variables. Critics have argued that such simple procedures are flawed because they fail to deal appropriately with the self-selection bias caused by selection on observables or unobservables present in observational data that is collected through household surveys (Imbens, 2004). For that reason, these studies fail to identify the causal effect of adoption (Rosenbaum, 2002; Imbens and Wooldridge, 2009). Propensity score matching (PSM) has been used to deal with the self-selection bias problem and estimate the average treatment effect *(*ATE*)* of technology adoption (Rosenbaum and Rubin, 1983). However, the PSM method also fails to deal appropriately with the problem of selection on unobservables by assuming that there are no unobserved differences between treatment and comparison group hence often implausible (Heckman et al., 1998). On the other hand, difference in difference approach eliminates fixed variation not related to treatment but can be biased if trends change and ideally requires two pre-intervention periods of data (Conley and Taber, 2011; Heckman et al., 1998).

Much of the work on propensity score analysis has focused on cases where the treatment is binary, but in many observational impact studies, treatment may not be binary or even categorical. In such cases, one may be interested in estimating the dose-response function (DRF) in a setting with a continuous treatment using a generalized propensity score (GPS) (Rosenbaum and Rubin, 1983). Following Rosenbaum and Rubin (1983) on propensity-score analysis, the GPS methodology was developed in 2004 by Hirano Imbens and Imai and van Dyk, Bia and Mattei (2008), as an extension to the propensity-score method (PSM) in a setting with a continuous treatment with unconfoundedness assumption. This allows removal of all biases in comparisons by treatment status as a result of adjusting for differences in a set of covariates.

Propensity score matching methodology has been the most widely used in empirical research. For instance, Kassie et al. (2011), Nabasirye et al. (2012), Amare et al. (2012), and Simtowe et al. (2012) focused on the comparison between adopters and non-adopters of various technologies. However, these studies did not consider the extent to which the benefits and the impact of level of adoption varied. Heckman et al. (1998), demonstrate that failure to compare participants and controls at the common propensity score is a major source of bias in evaluations. Nevertheless, effects of adoption are unlikely to be homogeneous but vary according to the intensity of adoption, hence adopters may not benefit in the same way from adoption. Recent studies by Bia and Mattei (2008), Kassie (2011, 2014), Kluve (2012), Liu and Florax (2014), Ouma et al. (2014), and Kreif (2015), applied GPS methodology to estimate heterogeneities in adoption impact. Similarly, the current study applied the GPS approach to evaluate whether the level of adoption of PPT has a beneficial effect on household welfare and the extent to which these benefits vary with the intensity of adoption.

In this study, household welfare was measured in terms of incomes, yield and poverty status whereby expenditure approach based on per capita food consumption was used to determine poverty indices. The dependent variable was area under PPT and the first step was to estimate the GPS, i.e. the conditional probability of receiving a particular level of treatment (intensity of adoption of PPT) given the observed covariates. This was estimated using maximum likelihood (ML) estimator using a Stata routine 'dose response'. Following Hirano and Imbens (2004), we define dose–response functions (DRF) in the potential outcomes framework (Rubin, 2005) as elaborated below. Suppose we have a random sample of units, indexed by $i = 1,..., N$. The continuous treatment of interest can take values in $t \in \tau$, where τ is an interval (t_0, t_1). For each unit, $Y_i(t)$ is the potential outcome for individual i under treatment level $t, t \in \tau$ where τ is an interval (t_0, t_1), and t denotes the dosage which in our case was the area under PPT. For each i there is a set of potential welfare outcomes $\{Y(t)i\}t \in \tau$ which is the individual level DRF. The key point of concern is the identification of the curve of average potential outcomes that is the entire average DRF, $\mu(t) = \mathrm{E}[Y_i(t)]$, which signifies the function of the average potential welfare indicator for PPT adopters. The observed variables for each unit i are a vector of covariates X_i (independent variables), the level of treatment received (land under PPT in acres), $T_i \in (t_0, t_1)$, and the potential outcome corresponding to the level of treatment received, $Y_i = (T_i)$. Notable is that the GPS methods are designed for analyzing the effect of a treatment level and therefore specifically refer to the sub-population of treated units/adopters (Bia and Mattei, 2008). This implies that including untreated units (non-adopters) might lead to misleading results (Guardabascio and Ventura, 2013). For that reason, the GPS results for this study focused on average DRF and marginal treatment functions for households who have adopted PPT whereas farmers who did not invest in the technology (untreated households) are not included in the GPS analysis.

The key identifying assumption in estimating the DRF is the weak unconfoundedness assumption; this assumption requires that for any level of treatment, the probability of receiving this level is independent of the potential outcomes, conditional on covariates, where the treatment assignment mechanism is independent of each potential outcome conditional on the covariates: $Y_i(t) \perp T_i \mid X_i$ for all $t \in \Gamma$ under unconfoundedness. The average DRF can be obtained by estimating average outcomes in sub-populations defined by covariates and different levels of treatment. Hirano and Imbens (2004) proved that GPS can be used to remove biases associated with differences in the observed covariates and that the DRF at a particular treatment level *t* can be estimated by using a partial mean approach in three steps below:

In the first step, we use the lognormal distribution to model the level of adoption of PPT (Ti) given the covariates:

$$\ln(\mathrm{T}_i) \mid \mathrm{X} \sim \mathrm{N}\left(\beta_0 + \beta_i^{'} \mathrm{X}_i, \delta^2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The parameters β_0, β_1 and δ^2 are estimated using maximum likelihood. The GPS ascertains that differences in covariates do not exist across treatment groups based on different areas allocated to PPT. Accordingly; the observed difference in welfare outcomes is attributable to different areas allocated to the technology. The GPS was estimated based on the parameter estimates in equation 2 as follows:

$$\hat{R} = \frac{1}{\sqrt{2\pi\hat{\delta}2}} \exp - \left(\frac{1}{\sqrt{2\pi\hat{\delta}2}} \left(\ln(\mathrm{T}_i) - \hat{\beta}_0 - \hat{\beta}_i^{'} \mathrm{X}_i \right)^2 \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

The second step involves estimating the conditional expectation of the outcome (household welfare) as a function of the intensity of the PPT (Ti) and estimated GPS ($\hat{R}_i$). As indicated by Hirano and Imbens (2004), the conditional expectation of the outcome can be estimated as a flexible function of treatment level and estimated GPS, which might also involve some interactions between the two. This study employed quadratic estimation:

$$\beta(t,r) = g\left(\left[\mathrm{Y}_i \mid \mathrm{T}_i, \hat{R}_i\right]\right) = \alpha_0 + \alpha_1 \mathrm{T}_i + \alpha_2 \hat{R}_i + \alpha_3 \mathrm{T}_i^2 + \alpha_4 \hat{R}_i^2 + \alpha_5 \mathrm{T}_i \hat{R}_i \ldots\ldots\ldots..(3)$$

Where *g* is a link function which is dependent on the household welfare outcome. Linear regression models were used, where welfare outcomes (household incomes, yield and poverty indices) were measured as continuous variables. The final step of the Hirano and Imbens' GPS methodology is the estimation of the DRF estimates that is the average expected conditional welfare outcomes in terms of yield, household incomes and poverty given the intensity of adoption and the estimated GPS. Therefore, the average DRF at a particular value of the treatment *t* was estimated averaging the (estimated) conditional expectation β(t,r) over the GPS at that level of treatment as follows:

$$\mu(t) = E(Y_i(t)) = \frac{1}{N} \sum_{I=1}^{N} g^{-1}\left(\hat{\alpha}_0 + \hat{\alpha}_i . t + \hat{\alpha}_2 . t^2 + \hat{\alpha}_3 . \hat{r}(t, \chi_i) + \alpha_4 . \hat{r}(t, \chi_i) 2 \alpha_5 x \hat{r}(t, \chi_i) \right) \ldots\ldots(4)$$

Where $\hat{\alpha}$ the vector of parameters estimated in the second stage and r (t, χ_i) is the predicted value of r(t, χ_i) at level t of the treatment. The entire DRF can then be obtained by estimating this average potential outcome for each level of area under PPT. We show plots of the average DRF and marginal treatment effect functions, defined as derivatives of the corresponding DRF's. The average DRF shows how the magnitude and the nature of the causal relationship between the area allocated to PPT and the welfare outcomes vary according to the values of the treatment variable, after controlling for covariate biases.

Marginal treatment effect function on the other hand shows the marginal effects of varying the area under PPT by a given unit on the welfare outcomes.

Poverty Decomposition model

The Foster, Greer and Thorbeecke (FGT) poverty index was used to determine poverty levels among the respondents (Foster and Thorbecke, 1984). Relative poverty[2] approach was considered while constructing the poverty line. A household was defined as poor if its consumption level was below this minimum. The relative approach that was adopted for this study takes a proportion of mean consumption expenditure as the poverty line. To develop an aggregate poverty profile for Uganda, Appleton's study used a large household survey dataset to estimate a consumption poverty line in Uganda shillings as UGX 15, 446 (USD 12.94) and UGX, 15,189 (USD12.71) per adult equivalent per month for eastern and rural Uganda respectively. Appleton also used a national average poverty line of UGX 16,643 (USD13.93) per person per month. The FGT poverty index is generally given as:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{Z - Y_i}{Z}\right)^{\alpha} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Where P is Foster, Greer and Thorbecke index ($0 \leq P \leq 1$), N is the total number of respondents, q is the number of respondents below the poverty line Z is the poverty line, and Y_i is per capita household expenditure of the i^{th} respondent. The analysis of the poverty status of the households were decomposed into the three indicators whereby when $\alpha=0$, P_0 gives the Incidence of Poverty (Headcount Index,); when $\alpha=1$, P_1 gives the Depth of Poverty (Poverty Gap,) and when $\alpha=2$, P_2 gives the Poverty Severity (Squared Poverty Gap). This study adopted Appleton's (1999) rural poverty line of USD. 12.71[3].

Tobit model: Estimation of intensity of adoption

Tobit model was used in the first stage as selection equation to estimate the intensity of adoption. Land size allocated to PPT was used as the dependent variable whereas explanatory variables included marital status, household size, gender, age, education level, farm labour, total land, farming system, total livestock units (TLU), access to extension service, access to credit, membership to group organization and distance to main road. The model is theoretically presented as follows (Greene, 2003);

$$Y^* = X\beta + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..6$$

Where Y^* is a latent variable that is unobservable, X is a vector of independent variables, β is a vector of unknown parameters, and ε is an error term that is assumed to be independently and normally distributed with zero mean and constant variance.

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[2] Relative poverty approach is based on cost of basic needs (CBN) approach in which some minimum nutritional requirement is defined and converted into minimum food expenses. To this is added some considered minimum non-food expenditure such as clothing and shelter (Ravallion and Bidani, 1994).

[3] The average exchange rate during the survey was 1 USD =UGX. 2,748

Data and description of variables

The study covered four districts of Eastern Uganda namely: Busia, Tororo, Bugiri and Pallisa. These are regions where striga weed, stemborer pests, poor soil fertility and unreliable rainfall are the major constraints to maize production. Besides, these are regions where PPT has been widely disseminated. Data used in this study was collected from 560 small-scale households between November and December 2014 through one-on-one interviews. Both PPT and non-PPT adopters were sampled. Both qualitative and quantitative data was collected.

Data was collected for a variety of variables including farm and farmer characteristics, maize yield, household incomes (both farm and non-farm), household expenditures (both food and non-food) as well as institutional attributes. Key household characteristics comprised of gender, age, household size, education level, total land owned, farming experience and livestock numbers. Total household expenditure data was adjusted for each household to arrive at per capita consumption expenditure which facilitated the determination of poverty indices. The treatment variable for the study was the area under PPT whereas outcome variables comprise incomes, maize yield, and poverty. Definitions of variables used in the analyses are presented in Table 1.

Table 1: Description of variables

Description	Variable type	Variable measurement
Outcome variables		
Intensity of PPT adoption	Continuous	Acres
Productivity	Continuous	Kgs/acre
Yield	Continuous	Kgs/unit area
Average incomes per annum	Continuous	Ugx
Household poverty status	Dummy	0=Non-poor; 1=Poor
Per capita expenditure	Continuous	Ugx
Independent variables		
Gender of household head	Dummy	0=Female; 1=Male
Age of household head	Continuous	years
Marital status	Categorical	1=Married;2=Single;3=Widowed;4=Divorced
Highest level of education of household head	Categorical	1= No formal education;2=Adult education;3=Primary school;4=Secondary school;5=Post secondary
Family size	Continuous	Number of persons
Family members above 18 years that offer farm labour	Continuous	Number of persons
Total land owned per household	Continuous	Acres
Kind of farming system practised	Categorical	1=Livestock farming;2=Crop farming;3=Mixed farming
Farming experience	Continuous	Years
Major source of income	Categorical	1=Farm incomes;2=Off-farm casual work;3=Off-farm permanent employment;4=Remittances

Total crop area	Continuous	Acres
Tropical Livestock Units	Continuous	Units
Access to agricultural extension services	Dummy	0=No;1=Yes
Field days/ demonstration Participation	Dummy	0=No;1=Yes
Access to credit	Dummy	0=No;1=Yes
Group membership	Dummy	0=No;1=Yes
Distance to nearest extension service provider	Continuous	Kilometers
Busia district	Dummy	0=No;1=Yes
Tororo district	Dummy	0=No;1=Yes
Bugiri district	Dummy	0=No;1=Yes
Pallisa district	Dummy	0=No;1=Yes

Results and discussion

Descriptive statistics

Majority of the respondents (50.2%) of the PPT adopters were female compared to non-PPT adopters whose majority were male (53.3%) (Table 2). The highest level of education was primary school for both adopters (52.5%) and non-adopters (61.8%), and the main occupation for household heads was farming (both crop and livestock farming). The average household size of PPT adopters was higher (8 members per household) compared to non PPT adopters (6 members per household). PPT adopters were significantly younger, with an average age of 38 years, compared to non-adopters who averaged 45 years. Additionally, adopters had significantly smaller pieces of land, average of 3.8 acres, compared to non adopters, with average land of 5.2 acres per household and less farming experience (17 years) compared to non-adopters with average of 22 years of farming experience. Whereas PPT requires extra labour for planting, maintenance and harvesting of desmodium and Napier grass, farmers can harvest more yield in a small piece of land under the technology (Khan et al., 2008a). The technology thus seems more attractive to younger farmers with relatively smaller pieces of land.

Table 2: Household socio-economic characteristics by adoption status

Variables	**PPT adopters**	**Non-PPT adopters**	**Chi. square test**
Gender (%)			0.82
Male	49.8	53.3	
Female	50.2	46.7	
Education level (%)			10.71**
No formal education	9.2	11.5	
Adult education	1	0	
Primary school	52.5	61.8	
Secondary school	29.4	24.8	
Post secondary education	7.9	1.8	
Main occupation (%)			5.19
Farming	93.3	90.8	
Salaried employment	1.8	3.9	

Self-employed off-farm	4.9	5.2	
			T.test
Household size	7.98	6.39	.24**
Family members above 18 years offering farm labor	2.83	2.38	1.21***
Average age of household head (years)	38.7	44.67	1.20***
Average land owned (acres)	3.8	5.15	.33***
Farming experience (years)	17.72	21.91	1.04***

NOTE: ****, **, Significant at 1, and 5% level respectively*

Source: Author's estimations from the survey data collected in 2014

The relationship between the level of PPT adoption and household incomes, per capita expenditure and maize yield is presented in Table 3. Households were sub-divided into quintiles based on the area of land allocated to PPT. Results shows that average household incomes, per capita food consumption, and yields increased with the expansion of land allocated to PPT.

Table 3: Level of PPT adoption, incomes, per capita food expenditure and yield

Quintiles of area under PPT (acres)	**Mean annual household incomes ('000 Ugx)**	**Per capita food consumption ('000 Ugx)**	**Yield (kgs)**
1	1,092.9	51.21	60
2	1,368.2	52.92	165
3	2,181.5	60.46	186
4	2,384.4	62.18	350

Productivity status for both adopters and non adopters

Productivity(kgs/acre)	**Minimum**	**Maximum**	**Mean**
PPT plots for adopters	800	1,433	988
Non-PPT plots for adopters	31	900	382
Non-PPT plots for non adopters	88	909	338

1:<=0.125, 2:>0.125<=0.25, 3:>0.25<=0.5, 4:>0.5

Source: Author's estimations from the survey data collected in 2014

Average maize productivity[4] for adopters was higher in push-pull plots (988kgs/acre) compared to non-PPT plots for the same farmers (adopters) with an average of 382kgs/acre. Statistical test showed that there was a significant difference in productivity for PPT plots and non-PPT plots for adopters (p=001). It was also noted that maize productivity from non-PPT plots amongst PPT adopters was higher than that from non-adopters (in non-PPT plots), which averaged 338 kgs/acre. This scenario is attributable to adopters having more information from the extension services, coupled with quality and reliable information offered through various dissemination pathways including field days , public meetings (*barazas*), farmer field schools, farmer teachers, and mass media (radio and print materials)

[4] Agricultural productivity is defined and measured in a number of ways including land productivity or yield. Productivity is output per unit of area cultivated commonly expressed in tons per hectare (t/ha) or kilograms per acre (kgs/acre) (Wiebe et al., 2001).

used by *icipe* and extension partners at different stages of dissemination and adoption process of PPT, and hence, they (adopters) are able to give proper management to even the areas where PPT is not being applied and get a better crop than the complete non-adopters (Amudavi et al., 2009; Murage et al., 2011, 2012).

Table 4 presents gender disaggregated mean difference of the impact of PPT adoption on household incomes as well as per capita consumption expenditure and productivity between adopters and non-adopters. While household income indicates the ability of the household to purchase its basic needs of life, per capita expenditure reflects the effective consumption of households and therefore provides information on the food security status of households (Nguezet, 2011).

Table 4: Gender disaggregated analysis of PPT adoption on welfare indicators

Variable	Adopters	Non adopters	Difference Test
Incomes (UGX)	1,388,032.97	1,048,072.08	339,960.89*
	(120,612.34)	(136,297.32)	(182,000.81)
Male	1,465,680.08	897,332.53	-568,347.55*
	(172,115.90)	(164,572.63)	(238,134.49)
Female	1,313,555.34	1,224,288.73	-89,266.40
	(171,750.21)	(223,959.65)	(280,765.93)
Per capita expenditure (UGX)	61,801.13	52,522.06	9,279.06
	(8,104.83)	(3,270.26)	(8,739.73)
Male	46,005.29	76,517.31	30,512.03*
	(3,276.38)	(14,381.11)	(14,749.61)
Female	59,006.24	44,982.63	-14,023.79*
	(5,702.39)	(5,118.23)	(7,603.87)
Productivity (Kgs/acre)	987.95	382.34	649.62***
	(6.94)	(13.05)	(14.78)
Male	969.22	326.48	-642.74***
	(9.20)	(16.58)	(18.96)
Female	1,006.49	351.88	-654.61***
	(10.29)	(20.58)	(22.99)

Results indicate that PPT adopters were better-off than non-adopters in terms of incomes and productivity; female adopters had higher per capita consumption expenditure at USD 21.47 (UGX.59,006) and maize productivity (1,006 kgs/acre) compared to their male counterparts with per capita consumption of USD 16.74 (UGX. 46, 005) and productivity of 969 kgs per acre. Notably, there was a significant difference between incomes and productivity of adopters and non-adopters, but with no significant difference in per capita consumption between the two groups. However, the differences in observed mean outcomes between adopters and non-adopters may not be attributed entirely to PPT adoption due to the problem of self-selection and non-compliance (Imbens and Angrist, 1994; Heckman and Vytlacil, 2005). The impact of the adoption of PPT on maize yield, incomes, and poverty is discussed in the sections that follow.

Econometric results

Determinants of intensity of PPT adoption: Tobit estimates

Tobit model results are presented in Table 5. From the findings, education level, farm labour, total land owned, livestock numbers (TLU), attendance and participation in field days and availability of extension services significantly influence the intensity of adoption. The results indicate that household heads with higher level of education adopted PPT. This can be inferred to imply that their views and mindsets enables them understand better and analyze benefits that come with the high-knowledge based technology whose immediate gains may not be visible. This is in line with the findings of Ferto and Forgacs, (2009), and Murage et al. (2015), which revealed that variation in education had a significant effect on perception of technology attributes given that more educated farmers are able to easily understand the benefits of a new knowledge-intensive innovation. Households size, with more family members who were above 18 years that offer farm labour, positively influenced the intensity of PPT adoption, a fact attributable to the labour-intensive nature of the technology, especially during the first season of land preparation, planting, and weeding, trimming and cutting back of desmodium and Napier grass (Khan et al., 2008b; De Groote et al., 2010).

A positive association between livestock numbers and intensity of PPT adoption implies that apart from reaping maize harvest from PPT plots, farmers have the benefit of reliable source of quality fodder from desmodium, Brachiaria and Napier grass, especially during the dry season. Hence the intensity of adoption increases with the total livestock units (TLU).

Table 5: Determinants of intensity of PPT adoption

Explanatory Variable	**Marginal effects**	**Std. Error**
Marital status	0.005	0.012
Household size	0.001	0.004
Gender	-0.007	0.016
Age	0.001	0.001
Education level	0.026**	0.007
Farm labour	0.190*	0.006
Total land	0.300**	0.001
Farming system	-0.001	0.001
TLU	0.005*	0.003
Extension service	0.260	0.033
Field day	0.052**	0.022
Credit access	0.004	0.015
Group membership	0.056***	0.020
Availability of extension service	0.000**	0.000
Distance to main road	0.001	0.001
Busia	0.079***	0.027
Tororo	0.077***	0.029
Bugiri	0.026**	0.028
Pallisa	0.067**	0.042
Model diagnostic		
Log likelihood	-1080.9834	
Pseudo R^2	0.083	
Prob > chi2	0.0005	
Number of observations	402	

NOTE: ***, **, *Significant at 1%, 5% and 10% level respectively

Besides, livestock may also be taken as a proxy of availability of manure which is an efficient alternative to chemical fertilizers. Results further show that farmers who were in close contact with agricultural extension officers increased the intensity of PPT adoption. PPT requires proper crop management practices hence the vital prerequisite of agricultural extension services. Agricultural extension is the most important source of information to farmers hence service providers should be able to avail research based information and educational programs to enable farmers understand a technology, make informed decisions and implement appropriate knowledge to obtain the best results (Agbamu, 2002; Long and Sworzel, 2007).

Results on covariate balancing are shown in Table 6, which presents balance statistics as mean differences (*t*-statistics) before and after adjustment with the GPS. After adjustment for the GPS, findings indicate that the covariate balance has clearly improved by the reduced number of *t*-values above 1.90. Generally, 27 variables had t-values greater than 1.90 before adjustment by GPS, while after adjustment these were reduced to 11 variables hence a reduction on the covariate imbalance.

Table 6: Covariate balancing for generalized propensity score matching: t statistics

Covariates	**Data after adjustment by GPS**				**Data before adjustment by GPS**			
	[.025,.028]	**[.03,.05]**	**[.056,.125]**	**[.126,1]**	**[.025,.028]**	**[.03,.05]**	**[.056,.125]**	**[.126,1]**
Marital status	-1.198	0.102	0.956	-0.448	-1.728	0.408	0.483	0.072
Household size	0.443	-1.829	1.491	**-2.147**	1.273	**-3.286**	**3.359**	-1.467
Gender	-1.204	-1.885	**2.416**	-0.742	**-2.841**	-1.361	**3.265**	0.673
Age	0.073	-1.604	**2.714**	-0.939	0.660	**-2.651**	**1.943**	-0.974
Education level	1.038	0.783	-0.400	-1.045	0.796	0.707	-0.656	-0.568
Farm labour	0.677	1.134	-0.906	-0.866	0.731	0.530	0.122	**-1.930**
Total land	0.321	-1.079	0.809	-0.568	1.252	0.357	0.526	**-2.151**
Farming system	-1.088	-1.672	1.630	-0.871	-1.119	0.146	**2.065**	**-2.242**
TLU	0.198	-0.264	0.146	-0.896	0.468	-0.794	-0.389	1.178
Extension service	-1.057	1.427	-1.091	0.352	0.074	0.914	-0.948	0.109
Field day	0.234	0.035	-0.168	1.378	**-1.905**	-0.122	1.247	-0.162
Credit access	-1.832	1.048	0.394	-0.347	**-2.619**	1.013	1.133	-0.935
Group membership	0.321	0.613	-0.007	0.556	0.028	0.969	0.184	-1.509
Distance to main road	0.911	0.616	-1.171	0.658	1.102	1.311	**-2.131**	0.483
Distance to extension service	0.878	1.049	-1.716	0.535	1.271	**1.930**	**-2.541**	0.140
Busia	-1.114	**-2.658**	**5.027**	**-3.551**	**-2.105**	-1.267	**4.172**	**-2.555**
Tororo	1.427	**-2.073**	**2.013**	0.205	**2.951**	**-3.563**	**2.017**	-0.535
Bugiri	1.825	**4.622**	**-7.942**	**2.507**	**3.291**	**6.147**	**-8.218**	0.752
Pallisa	-1.091	-0.164	1.026	1.387	**-4.508**	-1.429	**2.000**	**2.313**

Impact of intensity of adoption: Generalized propensity score

The GPS results in Table 7 show that gender, total land owned, participation and/or attendance of field days, and membership to community organizations had a significant influence on the intensity of adoption. If a farmer was a member to a community organization and/ or attended field days, he/she was more likely to gather information about the technology from other farmers, farmer teachers, and agricultural extension officers and hence intensified adoption of PPT. Additionally, extension service providers availed technical advice as well as farm inputs. This agrees with Kassie et al. (2012), who observed that with scarce or inadequate information sources coupled with imperfect markets and transactions costs, social networks such as farmers' associations or groups facilitate the exchange of information.

Table 7: Estimation of propensity score: Generalized Propensity Score

Explanatory variables	Average marginal effects	Std. Err
Marital status	0.014	0.074
Household size	0.016	0.022
Gender	-0.183*	0.098
Age	-0.002	0.005
Education level	0.063	0.042
Farm labour	0.042	0.034
Total land	-0.027***	0.007
Farming system	0.001	0.006
TLU	-0.017	0.018
Extension service	-0.063	0.209
Field day	0.314**	0.134
Credit access	0.018	0.094
Group membership	0.234*	0.124
Distance to main road	0.003	0.006
Distance to extension service	0.000	0.001
Busia	0.036*	0.129
Tororo	0.105**	0.142
Bugiri	0.605***	0.178
Pallisa	0.511***	0.169

NOTE: ***, **, *Significant at 1%, 5% and 10% level respectively

A negative significant relationship of gender means that being female increased the intensity of PPT adoption. This corroborates the findings of Murage et al. (2015), who observed that a higher percentage of women perceived PPT as a very effective strategy compared to men, a fact attributable to the technology characteristics that seemed to favor women's preferences, and hence more women are likely to intensify adoption than men.

Impact of adoption intensity on welfare outcomes: Dose-response function (DRF) estimates

Figures 1 to 4 show the DRF estimates and their derivatives that is the Marginal Treatment Function (MTF) of the impact of intensity of adoption on maize yield, household incomes, per capita consumption and poverty. The results clearly depict that there exists a significant and positive average effect of the intensity of adoption of PPT on maize yield, household incomes and per capita consumption expenditure, whereas poverty levels decline significantly. It is evident from the results that the average maize yield increases from 27 kgs at 0.025 acre to 1,400 kgs at 1 acre PPT adoption level. The average household income increases from 135 USD (UGX 370,000) at 0.025 acre to 273 USD (UGX 750,000) at 1 acre PPT adoption point whereas per capita food consumption increases from 15 USD (UGX 40,000) at 0.025 area share to 27 USD (UGX 75,000) at 1 acre. Additionally, there is a clear indication that the extent of poverty declines significantly with the intensity of adoption whereby the DRF estimate of the impact of intensity of PPT adoption on poverty as shown in Figure 4 confirms that probability of being poor declines from 48% at 0.025 acre to 28% at 1 acre PPT adoption level. The marginal treatment effects corresponding to maize yield, household incomes, and per capita consumption expenditure was positive and increased with a unit increase in area under PPT.

Nabasirye, (2012) using binary PSM methodology found similar results where adoption of improved maize technology had a positive significant effect on yields hence positive implications for food security and poverty alleviation in Uganda. In addition, Kassie et al. (2014) results from GPS analysis indicated that as households expand land area under improved maize technology, their food security status significantly improves while the extent of poverty declines in rural Tanzania.

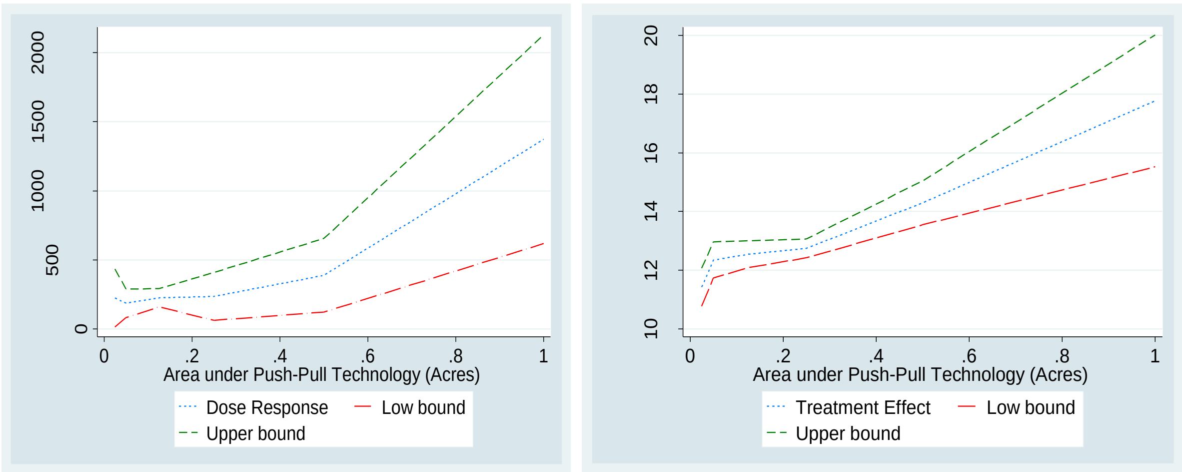

Figure 1: Impact of intensity of PPT adoption on maize Yield: Estimated dose response function and marginal treatment effect

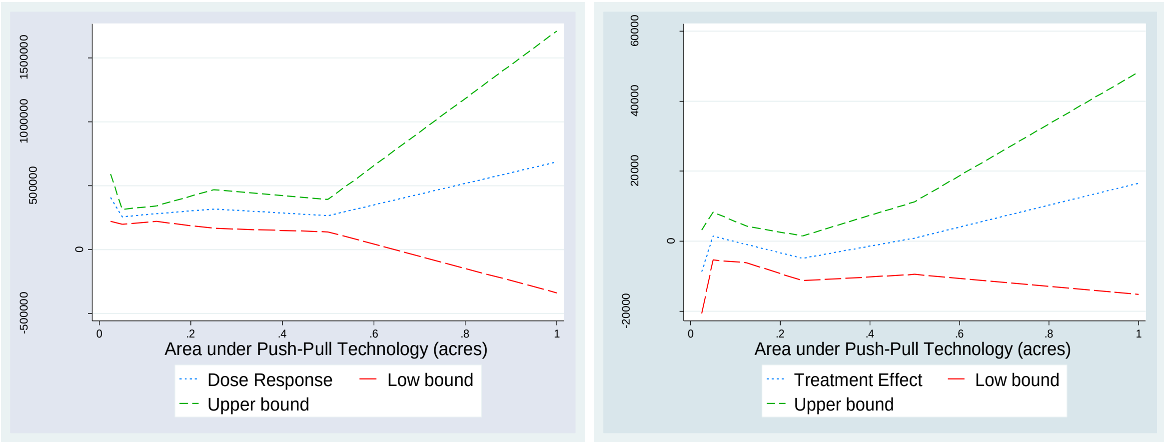

Figure 2: Impact of intensity of PPT adoption on household income: Estimates dose response function and marginal treatment effect

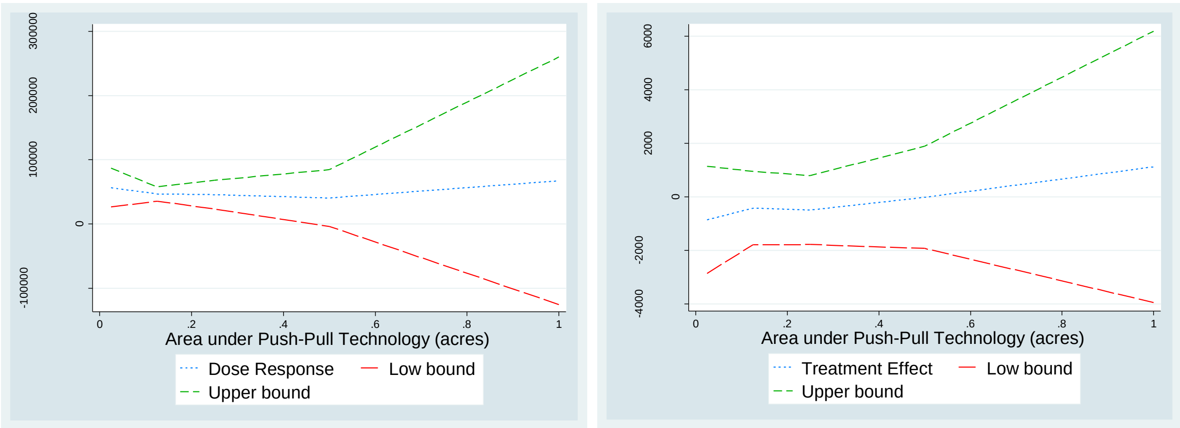

Figure 3: Impact of intensity of PPT adoption on per capita consumption expenditure: Estimated dose response function and marginal treatment effect

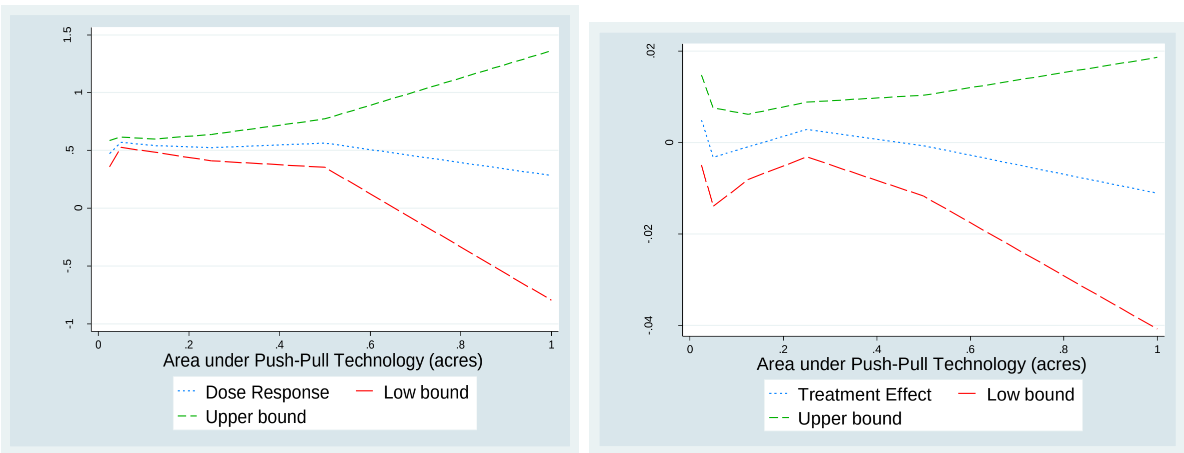

Figure 4: Impact of intensity of PPT adoption on poverty: Estimated dose response function and marginal treatment effect

Conclusions and Implications

There has been a growing demand for and stronger emphasis on impact assessment of agricultural technologies over the years to respond to various stakeholders' requirements, and increase the accountability and effectiveness of agricultural technology adoption. The objective of this paper was to evaluate the impact of intensity of PPT adoption on the welfare of smallholder farmers. Descriptive statistics results showed that the average yield, average household incomes, and average per capita food consumption increased with the expansion of land allocated to PPT. This is attributable to the extension services coupled with quality and reliable information offered through various dissemination pathways. PPT adopters were better-off than non-adopters in terms of incomes and productivity. The fact that female adopters had higher per capita food consumption and productivity compared to their male counterparts implies that, PPT is suitable for women who are the majority farmers, and who are often sidelined by new innovations. Efforts to promote PPT will therefore not only benefit farmers in general, but women in particular, therefore benefiting the entire farm families. Thus, agricultural policies and strategies targeting farm household food security and poverty reduction in maize-based systems should encourage PPT adoption.

Smallholder farmers with higher education levels, access to family labor, smaller land sizes and who owned livestock were more likely to adopt PPT. Moreover, attendance and participation in field days and availability of extension services increased the intensity of adoption, which further increased productivity and incomes but reduced poverty levels. These results are important for the technology promoters as they can be used to enhance targeting of the smallholder farmers. Impact results from GPS dose-response function estimates revealed a positive and significant average effect of the intensity of PPT adoption on yield, incomes, and per capita consumption and a negative average effect of the level of adoption on poverty. These results provide a robust confirmation on the impact of PPT on rural poverty in Uganda, with opportunities to enhance this impact by encouraging not only adoption but also allocation of more land to the technology. This then calls for more support in terms of extension service provision with respect to proper crop management practices. To establish whether results persist over time, future analysis using panel data may be of importance to control for unobserved heterogeneity and to observe the relationship between PPT adoption and poverty status. There is also need to establish the contribution of PPT to food security by use of subjective assessments.

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