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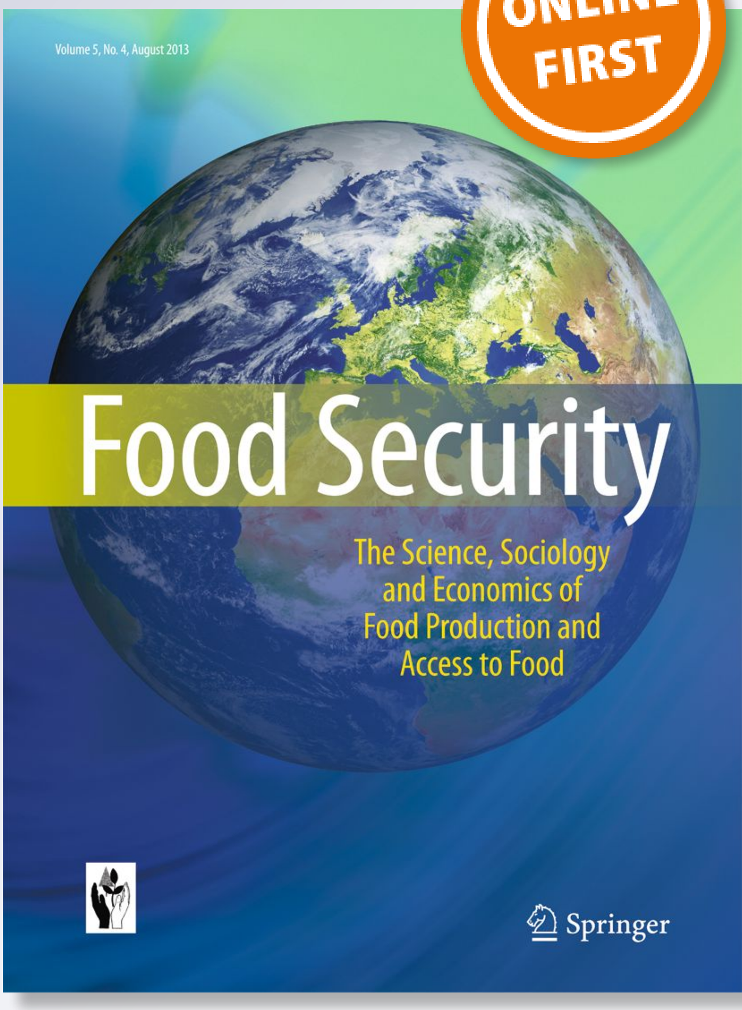

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ORIGINAL PAPER

Impact assessment of push-pull pest management on incomes, productivity and poverty among smallholder households in Eastern Uganda

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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. Push-pull is a habitat management strategy for the integrated management of stemborers, striga weeds and poor soil fertility involving the use of a natural repellent (push) and an attractant (pull). This biological technology simultaneously reduces the impact of three major production constraints to cereal-livestock farming in Africa − pests, weeds and poor soil. Cross sectional survey data were collected from 560 households in four districts in the region (Busia, Tororo, Bugiri and Pallisa), in November and December 2014. Generalized propensity scoring (GPS) was used to determine the intensity of adoption of the technology (i.e., land area allocated to PPT) and also to estimate the dose-response function (DRF) relating intensity of adoption and household welfare. Results revealed that with increased intensity of reported adoption of PPT, the probability of being poor declined through increased maize yield per unit area, incomes, and per capita food consumption. However, its impact varied with the intensity of adoption. With an increase in the area allocated to PPT from 0.025 to 1 acre, average maize yield per unit area increased from 27 kg to 1400 kg, average household income increased from 135 US$ (Uganda Shilling (USh) 370,000) to 273 US$ (USh 750,000) and per capita food consumption increased from 15 US$ (USh 40,000) to 27 US$ (USh 75,000). The average probability of a household being poor (below a rural poverty line of US$ 12.71) declined from 48% to 28%. These findings imply that increased investment in the dissemination and expansion of PPT is essential for poverty reduction among smallholder farmers in Uganda.

Keywords Push-pull technology · Adoption · Cereal-livestock · Dose-response · Household welfare · Uganda

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1 Introduction

Agricultural productivity is one of the key determinants of agricultural growth (Salami et al. 2010). Progress towards food and nutritional security requires that food is available, accessible and of sufficient quantity and quality (Mellor 1966; FAO 2012). Although an increase in agricultural productivity is a necessary condition for progress with the reduction of poverty and hunger, it is not sufficient, especially when there are rapidly growing human populations. Hence, inclusive agricultural growth that promotes equitable access to food, assets and resources for poor and vulnerable people is key. This is particularly so in the developing world where most of the poor and hungry live in rural areas, and where family farming and smallholder agriculture is the prevailing mode of farm organization (FAO 2012; AGRA 2013). Growth in smallholder family farming through increases in the productivity of labour and land 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 (*Sorghum bicolor* (L.) Moench), and rice (*Oryza sativa* L.)

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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; AGRA 2013). Despite the importance of cereal crops in the region, yields on smallholder farms are often very low and attributable to many negative abiotic and biotic constraints faced by farmers (Smil 2000). Stemborer pests, striga weeds, and low soil fertility have been ranked as some of the most important constraints to the efficient production of cereal crops by smallholders in SSA (Khan et al. 2014). In response to the challenges posed by these production constraints, the International Centre of Insect Physiology and Ecology (ICIPE) in collaboration with other partners developed a habitat management strategy for the integrated management of stemborers, striga weeds and poor soil fertility. The technology simultaneously manages those three key constraints to cereal cropping, and is known as 'Push-Pull' Technology (PPT) (Khan et al. 1997, 2001; Kfir et al. 2002). 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 the intercrop (Khan et al. 2001, 2014; Midega et al. 2010). Desmodium repels stemborer moths ('push'), while the surrounding grass attracts them ('pull') (Khan et al. 2001). In addition, desmodium suppresses the parasitic weed *Striga hermonthica* through two mechanisms; by stimulating suicidal germination of striga seeds and inhibiting growth of the radicle (Tsanuo et al. 2003; Hooper et al. 2009, 2010). This combination provides a novel means of *in situ* reduction of the striga seed bank in soils. However, the most important effect is allelopathy (root-to-root interference) (Khan et al. 2008b; Midega et al. 2010). Farmers practicing PPT have increased their maize and fodder yields, improved milk production and raised soil fertility (Khan et al. 2008a; Midega et al. 2015). Being a legume, desmodium adds nitrogen to the soil, which is an essential nutrient for crops. Desmodium also acts as a protective covering on the soil, retaining moisture, reducing soil erosion and improving water use efficiency (Khan et al. 1997, 2001; Midega et al. 2010).

Maize yield losses caused by stemborers can be 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 (De Groote 2002; Khan et al. 2008b; Nambafu et al. 2014). With a 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 US$ 14 billion annually in SSA, have mostly affected resource poor subsistence farmers resulting in high prevalence of food insecurity, malnutrition and poverty (Hassan et al. 1994; Kfir et al. 2002; Khan et al. 2014). Consequently, in an effort to expand the technology in several East Africa countries (including Uganda, Ethiopia, and Tanzania), thousands of farmers have been trained in PPT and currently the technology has been adopted by over 147,000 smallholder farmers in East Africa (Murage et al. 2012, 2015b; http://www.push-pull.net/3.shtml).

Although Uganda has been considered self-sufficient in food production nationally and is 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 many constraints, including the ones mentioned earlier (Bahiigwa 1999, 2004; Ssewanyana and Kasirye 2010; Mukhebi et al. 2011; Turyahabwe et al. 2013).

While there are many published studies on many aspects of PPT, very little has been published about its impact on household welfare, including poverty reduction and improvement in incomes. Most of the previous studies have considered the perception of the technology based on the principles of the beneficiary assessment approach (Fischler 2010). The beneficiary assessment approach assesses the value of an intervention as perceived by the beneficiaries and by gaining their views about an intervention (Salmen 1995). This approach is mainly used by project management as a design, monitoring, and evaluation tool. The current study deviates from this approach and instead evaluates the empirical questions of whether the intensity of adoption of the technology has improved the welfare of farmers by fundamentally assessing and understanding the significant changes that have taken place as a result of using PPT.

2 Data and description of variables

After PPT was initially pioneered and promoted in Kenya in 1997 (Gatsby Occasional Paper 2005), staff at ICIPE linked with partners to launch the technology in other East African counties, including Uganda. The process of out-scaling PPT was initiated in the striga-infested districts of Eastern Uganda in 2001. The districts included Kapchorwa, Budaka, Busia, Bugiri, Iganga, Tororo, and Pallisa (Gatsby Occasional paper 2011). The present study covered the four districts of Bugiri, Busia, Pallisa, and Tororo in Eastern Uganda. These are regions where striga weed, stemborer pests, poor soil fertility and unreliable rainfall are the major constraints to maize production. These are also regions where PPT has been widely disseminated and where rural farm families directly benefit through improved cereal–livestock productivity and incomes, reduced water run-off and soil erosion, enhanced soil fertility, minimized use of agrochemicals, improved food security and increased household income (Khan et al. 2008c, 2011; http://www.push-pull.net/adoption.shtml). Cross sectional data used in this study were collected from 560 small-scale households between November and December 2014 through one-on-one interviews. Both adopters[1] of PPT and non-adopters were sampled. Qualitative and quantitative data were collected.

Data were obtained 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 gender, age, household size, education level, farm size, farming experience and livestock numbers. Total household expenditure data were 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 land area under PPT whereas outcome variables comprised incomes, maize yield, and poverty. Explanatory variables used in the adoption estimation were grouped into household, farm, and institutional characteristics. Definitions of variables used in the analyses are presented in Table 1.

3 Analytical framework

Several studies have assessed the impact of technology adoption by examining the differences in mean outcomes of adopters and non-adopters, or by 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 of observables or unobservables present in observational data collected through household surveys (Guido 2004). For that reason, these studies failed to identify the causal relationship between treated and comparison groups (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) on outcomes (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 groups, which is often implausible (Heckman et al. 1998). On the other hand, a 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 (Heckman et al. 1998; Conley and Taber 2011).

Much of the work on propensity score analysis has focused on cases where the treatment is binary, but in many observational impact studies a treatment may not be binary or even categorical. In such cases, there may be interest 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 by Hirano and Imbens (2004) and Imai and van Dyk (2004) as an extension to the propensity-score method (PSM) in a setting with a continuous treatment and an unconfoundedness assumption. This allows the removal of all biases in comparisons by treatment status as a result of adjusting for differences in a set of covariates.

Propensity score matching has been most widely used in empirical research for binary treatments. 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 (a comparison between benefits accrued from technology adoption and the size of land allocated to the technology in acres) varied. Given that effects of adoption are not likely to be homogenous but vary according to the intensity of adoption (i.e. area allocated to push-pull), there is need to evaluate different intensities of adoption since adopters may not benefit the same way from adoption. Heckman et al. (1998) demonstrated that failure to compare participants and controls at the common propensity score is a major source of bias in evaluations. Recent studies by Bia and Mattei (2008), Kassie et al. (2011, 2014), Kluve et al. (2012), Liu and Florax (2014), Ouma et al. (2014), and Kreif et al. (2015) have applied GPS methodology to estimate heterogeneities in adoption impact. Similarly, in our study we applied the GPS approach to evaluate whether the level of adoption of PPT had a beneficial effect on household welfare and the extent to which these benefits varied with the intensity of adoption.

In this study, household welfare was measured in terms of incomes, crop yield, and poverty status. An expenditure approach based on per capita food consumption was used to determine poverty indices. The dependent variable was the 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 a maximum likelihood (ML) estimator using gpscore, and a Stata routine 'dose response'. The GPS methodology has advantages compared to other econometric techniques. It allows for continuous treatment, i.e., different levels of the adoption intensities, proxied by land allocated for PPT. In this way, we were able to determine the causal relationship between the outcome and the size of land allocated for PPT (level of adoption intensity). Thus, it enables identification of the entire function of the outcome over all possible values of the continuous treatment variable. Despite these advantages, GPS methods do not directly account for the unobservable variables that may affect both the outcome variables and the choice of technology A key assumption in the STATA-implemented version of the GPS

[1] Within the context of this research, adopters are farmers who have decided to exploit the full potential of the push-pull technology for management of striga weeds and stemborer pests, and also to boost soil fertility

Table 1 Description of variables used in the Push-Pull (PPT) study in Uganda

Description	Variable type	Variable measurement
Outcome variables		
Intensity of PPT adoption	Continuous	Acres
Productivity	Continuous	Kg/acre
Yield	Continuous	Kg/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
Farm size 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

method is the normality of the treatment variable conditional on the pre-treatment covariates. The application in our study assumed that the log transformation of the treatment (land area under PPT) has a normal distribution, given the covariates.

Following Hirano and Imbens (2004), in this study dose–response functions (DRF) were defined in the potential outcomes framework (Rubin 2005) as elaborated below. Suppose a random sample of units is indexed by $i = 1, \ldots, N$. The continuous treatment of interest can take values in $t \in \tau$, where τ is an interval (t_0, t_1). For each unit, $\Upsilon_i(t)$ 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 concern is the identification of the curve of average potential outcomes that is the entire average DRF, $\mu(t) = E[\Upsilon_i(t)]$, 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, $\Upsilon_i = (T_i)$. The GPS methods are designed for analyzing the effect of a treatment level and therefore specifically refer to the sub-population of treated units or 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: $\Upsilon_i(t) \perp T_i \mid X_i$ 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:

$$\ln(T_i)|X \sim N\left(\beta_0 + \beta_i' X_i, \delta^2\right) \tag{1}$$

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 Eq. 2 as follows:

$$\hat{R} = \frac{1}{\sqrt{2\pi\hat{\delta}2}} \exp-\left(\frac{1}{\sqrt{2\pi\hat{\delta}2}}\left(\ln(T_i) - \beta_0 - \hat{\beta}_i \hat{X}_i\right)^2\right) \tag{2}$$

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:

$$\begin{aligned}\beta(t,r) = g\left(\left[Y_i|T_i,\hat{R}_i\right]\right) = \alpha_0 + \alpha_1 T_i \\ + \alpha_2 \hat{R}_i + \alpha_3 T_i^2 + \alpha_4 \hat{R}_i^2 + \alpha_5 T_i \hat{R}_i\end{aligned} \tag{3}$$

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:

$$\begin{aligned}\mu(t) &= E(Y_i(t)) \\ &= \frac{1}{N}\sum_{I=1}^{N} g^{-1}\left(\hat{\alpha}_0 + \hat{\alpha}_i \cdot t + \hat{\alpha}_2 \cdot t^2 + \hat{\alpha}_3 \cdot \hat{r}(^t, x_i) + a_4 \cdot \hat{r}(^t, x_i) 2 a_5 x \hat{r}(^t, x_i)\right)\end{aligned} \tag{4}$$

Where $\hat{\alpha}$ the vector of parameters estimated in the second stage and r (t, x_i) is the predicted value of r (t, x_i) at level t of the treatment. The entire DRF can then be obtained by estimating this average potential outcome for each level of land under PPT. We show plots of the average DRF and marginal treatment effect functions, defined as derivatives of the corresponding DRFs. 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.

3.1 Poverty decomposition model

The Foster, Greer and Thorbeecke (FGT) poverty index was used to determine poverty levels among the respondents (Foster et al. 1984). A 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 (Ssewanyana and Kasirye 2013) used a large household survey dataset to estimate a consumption poverty line in Uganda Shillings as USh 15,446 (US$ 12.94) per adult equivalent per month for eastern Uganda and USh 15,189 (US$ 12.71) for rural Uganda. Appleton also used a national average poverty line of USh 16,643 (US$ 13.93) per person per month. The FGT poverty index is generally given as:

[2] A relative poverty approach is based on the 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 for clothing and shelter (Ravallion and Bidani 1994).

Table 2 Household socio-economic characteristics by adoption status for Push-Pull technology (PPT) in Uganda

Variables	PPT adopters ($N = 400$)	Non-PPT adopters ($N = 160$)	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 farm size owned (acres)	3.8	5.15	.33***
Farming experience (years)	17.72	21.91	1.04***

Source: Authors' estimations from the survey data collected in 2014

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

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

where P is Foster, Greer and Thorbecke index ($0 \le P \le 1$), N is the total number of respondents, Z is the poverty line, q is the number of respondents with incomes at or below 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 was 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 (2009) rural poverty line of US$ 12.71.[3]

4 Results and discussion

4.1 Descriptive statistics

Household socio-economic characteristics by adoption status are presented in Table 2. The majority of the Push-Pull (PPT) adopters were female (both female household heads and female spouses), compared to non-adopters of PPT who were mainly male. Adopters of PPT were significantly younger compared to non-adopters, and adopters had smaller pieces of land compared to non-adopters. Although PPT requires extra labour for planting, maintenance and harvesting of desmodium and Napier grass, farmers can harvest a greater maize yield on a small piece of land using the technology (Khan et al. 2008a). PPT thus seems more attractive to younger farmers with relatively smaller pieces of land.

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 quartiles based on the area of land allocated to PPT. Average household incomes, per capita food consumption and maize yield (kg grain per unit land area) increased with the expansion of land allocated to PPT.

Average maize productivity[4] for adopters was higher in PPT plots of land (988 kg/acre) compared to non-PPT plots for the same farmers (adopters) which averaged 382 kg/acre. Statistical tests showed that there was a significant difference in productivity between PPT plots and non-PPT plots for adopters ($p = 001$). Maize productivity from non-PPT plots amongst adopters of PPT was higher than that from non-adopters (in non-PPT plots), which averaged 338 kg/acre. This finding can be attributed to adopters having more information from extension services,

[3] The average exchange rate during the survey was 1 US$ = USh 2748

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

Table 3 Level of Push-Pull technology (PPT) adoption, incomes, per capita food expenditure and maize yield in Uganda

Quartiles of area under PPT (acres)	Mean annual household incomes ('000 USh)	Per capita food consumption ('000 USh)	Maize yield (kg/unit area)
1	1092.9	51.21	60
2	1368.2	52.92	165
3	2181.5	60.46	186
4	2384.4	62.18	350
Productivity status for both adopters and non adopters			
Productivity (kg/acre)	Minimum	Maximum	Mean
PPT plots for adopters	800	1433	988
Non-PPT plots for adopters	31	900	382
Non-PPT plots for non adopters	88	909	338

Source: Authors' estimations from the survey data collected in 2014

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

coupled with quality and reliable information offered through dissemination pathways including field days, public meetings (*barazas*), farmer field schools, farmer-teachers, and the mass media (radio and print materials) used by ICIPE and extension partners at different stages of the dissemination and adoption process with PPT. Hence, the adopters were able to provide better management to even those areas of land where PPT was not used and obtain a better crop than complete non-adopters (Amudavi et al. 2009; Murage et al. 2011, 2012).

Table 4 presents a gender disaggregated mean difference of the impact of PPT adoption on household incomes, and 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 for life, per capita expenditure reflects the effective consumption of households and therefore provides information on the food security status of households (Nguezet et al. 2011).

Results indicated that adopters of PPT were better-off than non-adopters in terms of incomes and productivity. Female adopters had higher per capita consumption expenditures calculated at US$ 21.47 (USh 59,006), and maize production (1006 kg/acre), compared to their male counterparts with per capita consumption of US$ 16.74 (USh 46,005) and productivity of 969 kg per acre. This agrees with the findings of Murage et al. (2015a) that more women were willing to continue to use PPT and to expand the technology. The increased use of PPT is a positive move towards reduction of the major constraints to cereal production, and a step towards increased food security. Notably, there was a significant difference between the incomes and productivity of adopters and non-adopters, but 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 the adoption of PPT 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 presented and discussed in the sections that follow.

4.2 Econometric results

To build confidence in the use of GPS due to its endogeneity limitation, we conducted a robustness check by applying the Hausman test (Chmelarova 2007; Adkins et al. 2012). That test ruled out the possibility of the existence of strong endogeneity between the intensity of PPT adoption and

Table 4 Gender disaggregated analysis of Push-Pull (PPT) adoption on welfare indicators in Uganda

Variable	Adopters	Non adopters	Difference test
Incomes (US$)	505.11	381.39	123.71*
	(43.89)	(49.60)	(66.23)
Male	533.36	326.54	−206.82*
	(62.63)	(59.89)	(86.66)
Female	478.00	445.52	−32.48
	−62.50	−81.50	−102.17
Per capita expenditure (US$)	22.49	19.11	3.38
	(2.95)	(1.19)	(3.18)
Male	16.74	27.84	11.10*
	(1.19)	(5.23)	(5.37)
Female	21.47	16.37	−5.10*
	(2.08)	(1.86)	(2.77)
Productivity (kg/acre)	987.95	382.34	0.24***
	(6.94)	(13.05)	(0.01)
Male	969.22	326.48	−0.23***
	(9.2)	(16.58)	(0.01)
Female	1006.49	351.88	−0.24***
	(10.29)	(20.58)	(0.01)

***, * Significant at the 1% and 10% levels respectively

Table 5 Covariate balancing for Generalized Propensity Score (GPS) matching, involving 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**
Farm size	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**
Tropical livestock unit	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**

Figures in bold shows variables with t-statistics > 1.90

membership of farmers' organizations (which had a *p*-value of 0.02, significant at 5%), and between owning more cattle (tropical livestock units, TLU[5]) and provision of extension services (which had p-value of 0.04, significant at 5%). These variables had small *p*-values (less than 0.05) and therefore this showed that the influence of any unobserved factors was negligible and the application of GPS was justified. Additionally, results on covariate balancing, which presents balance statistics as mean differences (*t*-statistics) before and after adjustment with the GPS, are in Table 5. Comparing the last four columns (raw or unadjusted data) in Table 5 with the first four columns of the same table (adjusted data) suggest that the covariate balance had improved after GPS adjustment. For instance, the first interval had 27 variables with a t-statistic greater than an absolute value of 1.90, without conditioning on the GPS, whereas, after adjusting with the GPS, this was reduced to 11 variables. In general, the covariate imbalance reduced by 65% after adjustment.

Table 6 Estimation of the Generalized Propensity Score in Uganda

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
Farm size	−0.027***	0.007
Farming system	0.001	0.006
Tropical livestock unit	−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

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

4.3 Impact of intensity of PPT adoption using the generalized propensity score

The GPS results in Table 6 show that gender, farm size, attendance at field days, and membership of community organizations had a significant influence on the intensity of adoption

[5] Total livestock unit was calculated as (1 for a bull +0.7 for a cow +0.5 for a heifer +0.5 for a young bull +0.3 for a calf +0.1 for a goat +0.1 for a sheep +0.05 for a duck +0.05 for a turkey +0.01 for a chicken +0.2 for a pig) (Otte and Chilonda 2002).

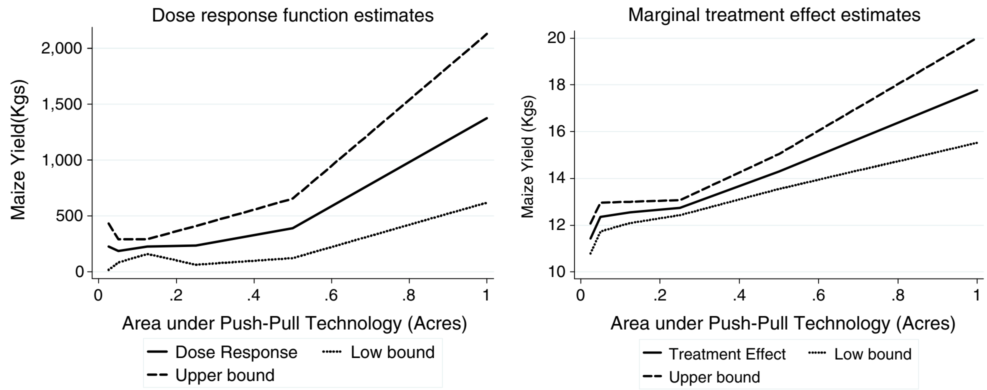

Fig. 1 Impact of intensity (land area) of Push-Pull technology (PPT) adoption on maize yield (kg maize grain/unit land area) in Uganda, using estimated dose response function and marginal treatment effect

(land allocated to PPT in acres). If a farmer was a member of a community organization or participated in field days, the farmer was more likely to gather information about the technology from other farmers, farmer teachers, and agricultural extension officers, and hence intensified their adoption of PPT. Additionally, providers of extension services gave technical advice as well as farm inputs. This agrees with Kassie et al. (2012) who observed that with scarce or inadequate sources of information, coupled with imperfect markets, and high transaction costs, social networks such as farmers' associations and groups facilitate the exchange of information.

The negative and significant relationship we found with gender means that being female increased the intensity of adoption of PPT. This agrees with Murage et al. (2015a), who observed that a higher percentage of women perceived PPT to be a very effective strategy compared to men. This may be because characteristics of the technology seemed to favor women's preferences, and hence more women are likely to intensify PPT adoption than men.

4.4 Impact of adoption intensity on welfare outcomes through dose-response function (DRF) estimates

Figures 1, 2, 3, and 4 show the dose-response function (DRF) estimates and their derivatives, including the Marginal Treatment Function (MTF) of the impact of intensity of adoption of PPT on maize yield, household incomes, per capita consumption and poverty. Adopting PPT improved household welfare through increased yield, incomes, per capita consumption and a decline in poverty, though its impact varied with the level of adoption. The results further showed a significant and positive average effect of the intensity of adoption of PPT on maize yield (expressed as kg grain/unit land area), household incomes and per capita consumption expenditure, whereas poverty levels declined significantly. The average production of maize increased from 27 kg (produced on 0.025 acre) to 1400 kg on one acre when PPT was adopted on an acre. Average household income increased from 135 US$ (USh 370,000) at 0.025 acre of PPT adoption to 273 US$ (USh 750,000) with 1 acre of PPT adoption, whereas per capita food consumption increased from 15 US$ (USh 40,000) at 0.025 area share to 27 US$ (USh 75,000) with 1 acre. Additionally, there was a clear indication that the extent of poverty declined significantly with the intensity of adoption; the DRF estimate of the impact of intensity of PPT adoption on poverty (Fig. 4) confirmed that the probability of being poor declined from 48% at 0.025 acre of PPT adoption to 28% when PPT was used on 1 acre. The marginal treatment effects corresponding to maize yield, household incomes, and per capita consumption expenditure were positive and increased with unit increase in the area under PPT.

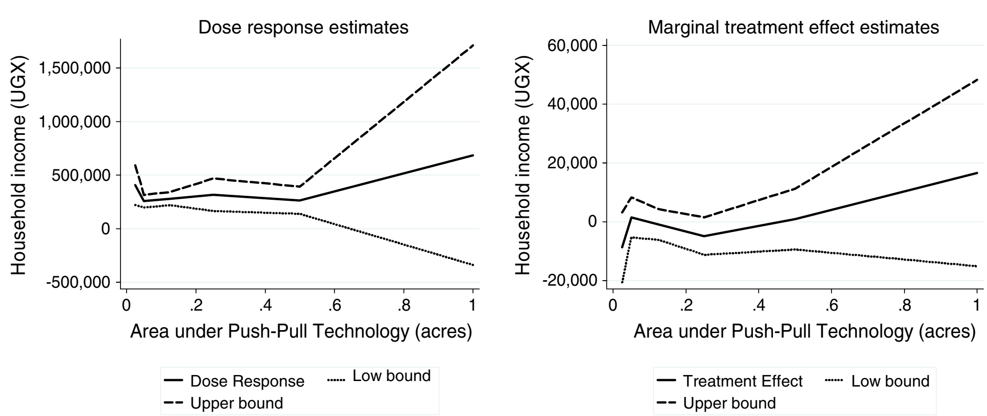

Fig. 2 Impact of intensity (land area) of Push-Pull technology (PPT) adoption on household income in Uganda shillings, using estimates of dose response function and marginal treatment effect

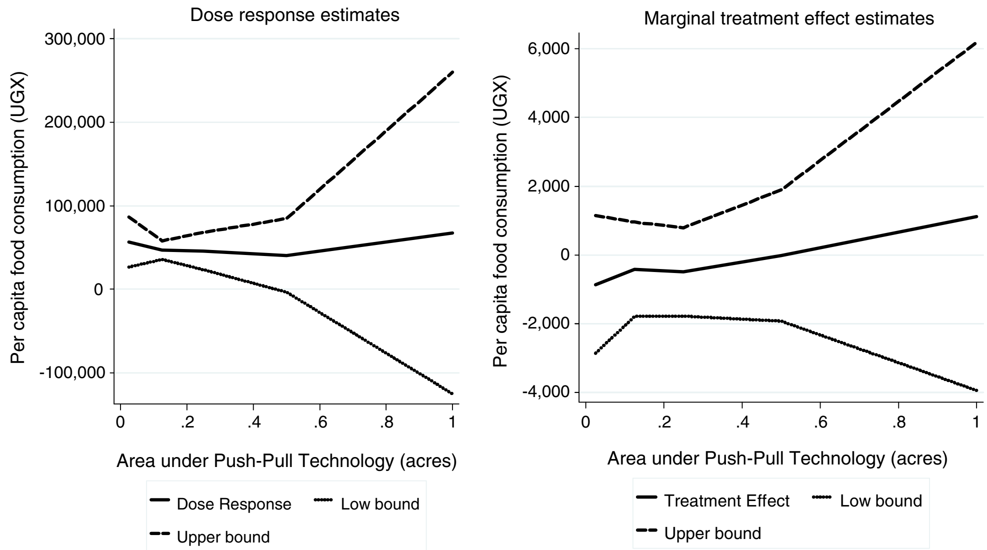

Fig. 3 Impact of intensity (land area) of Push-Pull technology (PPT) adoption on per capita food consumption expenditure in Ugandan shillings, using estimated dose response function and marginal treatment effect

Nabasirye et al. (2012), using binary PSM methodology, found similar results to ours where adoption of 'improved' maize technology had a positive effect on crop yields in Uganda. Their results showed that on average, the increase in maize yields after adoption of improved seed was 371 kg/acre using the Epanechnikov kernel matching algorithm and 359 kg/acre using the radius matching algorithm, with positive implications for food security and poverty alleviation in Uganda. In addition, results by Kassie et al. (2014) from GPS analysis indicated that, on average, as households expand the land area under improved maize technology, from one acre to 10 acres, the probabilities of chronic and transitory food insecurity reduced between 0.7 and 1.2% and between 1.1 and 1.7%, respectively while the extent of poverty declined in rural Tanzania.

5 Conclusions and implications

There has been a growing demand for, and a stronger emphasis on, impact assessment of agricultural technologies over recent years to respond to the requirements of various stakeholders, and to increase the accountability and effectiveness of agricultural technology adoption. The aim of such work is to evaluate and understand whether agricultural technologies achieve anticipated outcomes.

The objective of this paper was to evaluate the impact of the intensity of Push-Pull (PPT) adoption on the welfare of smallholder farmers in Uganda. The average maize grain yield (kg/unit land area), average household incomes and average per capita food consumption increased with the expansion of land allocated to PPT. Additionally, adopters of PPT were better-off than non-adopters in terms of incomes and crop production. Gender, education level, access to family labor, small land sizes, participation in field days and availability of extension services all increased the intensity of adoption (as indicated by land in acres allocated to PPT), which further increased productivity and incomes, but reduced poverty. These results are important for the promoters of agricultural technology as factors that significantly influence the intensity of adoption can be used to target smallholder farmers. GPS

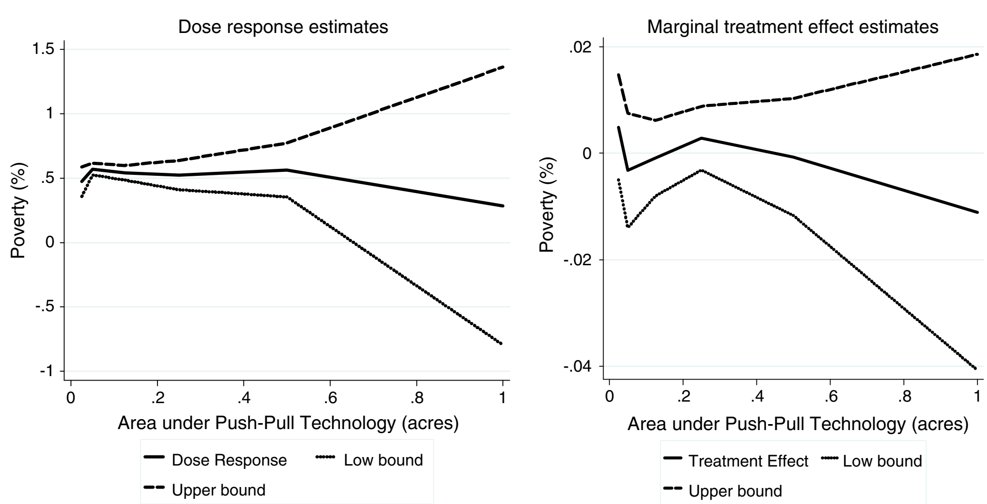

Fig. 4 Impact of intensity (land area) of PPT adoption on changes in poverty (based on food consumption expenditures) in Uganda, using estimated dose response function and marginal treatment effect

dose-response function estimates revealed a positive and significant average effect of the intensity of PPT adoption on maize yield in kg per unit area of PPT, incomes, and per capita consumption. There was an important negative average effect of the level of adoption on poverty. Our results provide a robust confirmation of the positive impact of PPT on rural poverty in Uganda, with opportunities to enhance this impact by encouraging more initial adoption and the allocation of more land to the technology by those that have already started to use it.

This then calls for additional support to provide extension services to help farmers use appropriate PPT crop management practices. Continued efforts to promote PPT will benefit farmers in general, but women in particular, and therefore benefit entire farm families. More broadly, agricultural policies and strategies that target farm household food security and poverty reduction in maize-based systems in Uganda and elsewhere should explicitly encourage the adoption of PPT. To establish whether these positive benefits of using PPT persist over time, future analysis using panel data may be important so as to control for unobserved heterogeneity and to observe the relationship between PPT adoption and poverty status. There is also a need to better establish the contribution of PPT to food security by use of subjective assessments in addition to objective measures. This will capture perceptions by respondents (through self-assessments) of their food security status due to their adoption of PPT.

Compliance with ethical standards

Conflict of interest The authors declare that we have no conflict of interest with the organization that sponsored the research work.

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Zeyaur Khan is recognized for his significant contribution to Africa by enhancing food security and environmental sustainability, through scientific research into the complex mechanisms that govern the ecology of plant–insect interactions and plant signaling in smallholder cereal–livestock production systems. This work led to the development of push-pull as an ecological, pro-poor agricultural innovation, and its adaptation to climate change to ensure its long term sustainability. He has also led a research-based extension system for wide-scale dissemination of push–pull, in which natural and social scientists work closely with farmers and extension agents to ensure that research serves the evolution and spread of the technology. Through his research and development work in Africa over the last 22 years, Prof Khan has shown that push-pull can sustainably increase food production without environmental damage. He has authored/co-authored over 100 scientific papers in refereed journals, as well as 10 book chapters, five books and several booklets and brochures.