Estimating the Adoption Rates of Two Contrasting Striga Weeds Control Technologies in Kenya

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Abstract

Pull-Pull (PPT) and *Imazapyr* resistant maize (IR) technologies are among the *Striga* weeds eradication innovations that have been promoted in western Kenya. In order to direct agricultural investment optimally, the most promising technology need to be identified and up scaled given limited financial and resource allocation trade-offs. Using data from a sample of 326 farmers, we applied the Average Treatment Effect (ATE) framework to estimate the actual and potential adoption rates of the two technologies. The results indicate relatively similar actual adoption rates of PPT (37%) and IR maize technology (36.3%). However, the potential adoption rates of PPT and IR maize technology were 56.3% and 46%, respectively, whereby the adoption gap of PPT (20%) was higher compared to that of IR maize technology (9%). These findings show that, if extra efforts are made to close the adoption gap to potential, PPT is a more attractive *Striga* control strategy.

Keywords: Push-Pull Technology, IR maize technology, adoption, Average Treatment Effect, Kenya

JEL: C13, O33, Q12, Q16

1 Introduction

Striga weeds, (*Striga hermonthica* (Del.) Benth and *Striga asiatica* [Scrophulariaceae] (L.) Kuntze) are considered the most important challenge in cereal production in Kenya (HASSAN et al., 1994). They are estimated to cause up to 100% yield loss which translates to a great cash income loss, food insecurity and poverty to the affected families (KHAN et al., 2001; KHAN et al., 2008a). It is in response to these challenges that the International Maize and Wheat Improvement Centre (CIMMYT), the International Centre of Insect Physiology and Ecology (ICIPE) and the Kenya Agricultural Research Institute (KARI) in collaboration with other stakeholders developed and promoted various technologies to aid in control of *Striga* weed. These technologies included Push-Pull Technology (PPT) and *Imazapyr* Resistant (IR) maize technology.

The PPT was developed by ICIPE in Kenya and Rothamsted Research Institute in the United Kingdom, in collaboration with other research organizations in Eastern Africa as a strategy to control cereal stemborers and *Striga* weed (KHAN and PICKETT, 2004). The technology uses *desmodium* (*Desmotium uncinatun)* which is intercropped with maize and produces repulsive smells to the stemborer moths thereby keeping them away from ovipositing eggs on maize. Napier grass which is planted as a perimeter in the maize fields attracts and kills most of the emerging larvae (KHAN et al*.,* 2001). *Desmodium* through root exudates limits the growth of *Striga* by causing abortive germination, improves soil fertility through nitrogen fixation and controls soil erosion (KHAN et al., 2007). The technology is suitable to smallholder mixed cropping systems in Africa and effectively addresses major production constraints thereby increasing maize yields from below 1 t/ha to 3.5 t/ha using locally available plants (KHAN et al., 2011).

The IR maize technology is commonly known as herbicide-coated maize or StrigAway technology which provides another option for farmers to suppress *Striga* and grow maize at the same time (KANAMPIU et al., 2002; ODHIAMBO and WOOMER, 2005). The technology involves coating of maize seeds with a systemic herbicide called *Imazapyr*. The IR maize technology was developed by CIMMYT in collaboration with Weizmann Institute of Science in Israel, KARI and Baden Aniline and Soda Factory (BASF) which is a chemical company. The technology has two important attributes: (a) herbicide resistant maize and (b) herbicide *(Imazapyr)* coating. As the maize seeds germinate, they absorb the herbicide. The germinated maize then produces a chemical which induces germination of the *Striga* weed, but as the *Striga* seedlings attach to the roots of the maize to withdraw nutrients, they are killed by the herbicide. The *Imazapyr* which is not absorbed by the maize seedling diffuses into the surrounding soil and kills un-germinated *Striga* seeds (KANAMPIU et al., 2002). The technology has been known to suppress *Striga* from emergence (KABAMBE et al., 2007).

Despite the imminent advantages of PPT and IR maize technology in the control of *Striga* weed, their adoption rate is still low. A study by KHAN et al. (2011) showed that, approximately 30,000 farmers in the East African region covering an area of about 15,000 hectares have adopted the technology. The number of IR maize technology adopters is however not known, but a study by MIGNOUNA et al. (2011a) showed that the uptake is still low. Understanding the divergence between actual and potential adoption rates of both technologies is critical in guiding the policy makers identify the effective and most promising technology. This study aimed at establishing the comparative advantage of adopting PPT or IR maize technology by smallholder farmers as *Striga* control innovations and determine which of the two technologies has the highest adoption potential, contingent on farmer resources and socio-economic factors. This would ensure optimal allocation of limited agricultural production resources.

We are unaware of any study that has compared the adoption rates of the two technologies conditional on competing resource demands and accounting for the fact that, the two technologies are more or less geared towards providing solution to a common problem (*Striga* control). The rest of the paper is organized as follows: in section 2, we present the empirical methods and data while we describe and discuss the results in section 3. Lastly, in section 4 we conclude and draw policy implications.

2 Empirical Method and Data

2.1 Analytical Strategy

The average treatment effect (ATE) according to DIAGNE (2006) and DIAGNE and DEMONT (2007), provides a framework for estimating the PPT and IR maize technology adoption rates and the determinants of the same. It is used to derive consistent nonparametric and parametric estimators of population adoption rates and their determinants, since commonly used adoption rates estimators, suffer from "nonexposure" bias or selection bias. A counterfactual outcome framework is used where every farmer in the population has two potential outcomes: with and without exposure to a technology. Exposure (awareness of a technology's existence) matters in a technology's adoption. This is due to the fact that, one cannot adopt a technology which he/she don't know if it exists. The exposure variable in this study accounts only for the mere knowledge of the existence of the technology, and only indicates whether or not the farmer is aware of the existence of the technology. The two technologies are disseminated in such a manner that, a farmer has limited or no chance of being exposed to both innovations. No demonstrations or on-farm trials had been carried out by respective technology staff in the same village. Therefore, a farmer has a low probability of being aware of both technologies. This study therefore, assumed that the two technologies were mutually exclusive.

Assuming that y_1 is the potential adoption outcome of a farmer when exposed to PPT or IR maize technology and y_0 the potential adoption outcome when not exposed to them. The potential adoption outcome of the two technologies can either be adoption status (a dichotomous 0, 1 variable) or a measure of intensity of adoption such as the total land area allocated to the innovations. The treatment effect for farmer i is measured by the difference $y_{i1} - y_{i0}$. Thus, the expected population adoption impact of exposure to these technologies is given by the expected value which is $E(y_1 - y_0)$ referred to as the ATE, and a measure of interest. It is however difficult to observe both an outcome and its counterfactual, and thus makes it impossible to measure $y_1 - y_0$ for any given farmer. However, since exposure is a necessary condition for adoption, we have $y_0 = 0$ for any farmer whether exposed to a set of new technologies or not. Hence the adoption impact of farmer *i* is given by y_{i1} and the average adoption impact is given by $ATE = Ey_1$.

Unfortunately, we observe y_1 only for farmers exposed to these technologies. Hence, we cannot estimate the expected value Ey_1 from the average of a randomly drawn sample, since some of the y_1 would be missing. The potential adoption rate gives a researcher an estimate of the adoption rate to be achieved once the whole population is made aware of the technology's existence. It does not necessarily have to be 100% since not all members of the population once exposed will adopt. Some chose not to adopt the technology even after being made aware although on average, the uptake levels in the treated villages are expected to be higher. The ATE generated estimators are classified under two broad classes: conditional independence assumption and instrumental variable methods (ROSENBAUM and RUBIN, 1983; WOOLDRIDGE, 2002).

Parametric Estimation of ATE

The parametric estimation procedure of ATE which holds under the conditional independence assumption is given by:

$$ATE_X = E(y_1 / x) = E(y / x, W = 1) \tag{1}$$

The estimation first specifies a parametric model for the conditional expectation in the right hand side of the second equality of the above equation which involves the observed variables *y, x* and *W*:

$$E(y / x, W = 1) = g(x, \beta) \tag{2}$$

g is a known function of the vector of covariates *x, W is* an indicator for exposure to PPT and IR maize technologies, where *W*= 1 denotes exposure and *W*= 0 otherwise, and β is an unknown parameter vector, which is to be estimated using standard Least Squares or maximum likelihood estimation (MLE) procedures. This is done using the observations from the sub-sample of farmers who are aware of the respective technologies. Given an estimated parameter $\hat{\beta}$, the predicted values $g(x_i, \hat{\beta})$ are computed for all the observations *i* in the sample (including the observations in the non-aware sub-population). Thereafter, the adoption rate within the whole population (ATE), adoption rate of the treated (exposed) sub-population (ATE1) and the adoption rate within the non-exposed sub-population (ATE0) are estimated by taking the average of the predicted $g(x_i, \hat{\beta})$ i = 1.....,n across the full sample (for ATE) and respective sub-samples (for ATE1 and ATE0):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \beta) \tag{3}$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n_e} W_i g(x_i, \beta) \tag{4}$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - W_i) g(x_i, \beta) \tag{5}$$

The marginal effects of the k dimensional vector of covariates x, at the average point ($\bar{x}$) are estimated as:

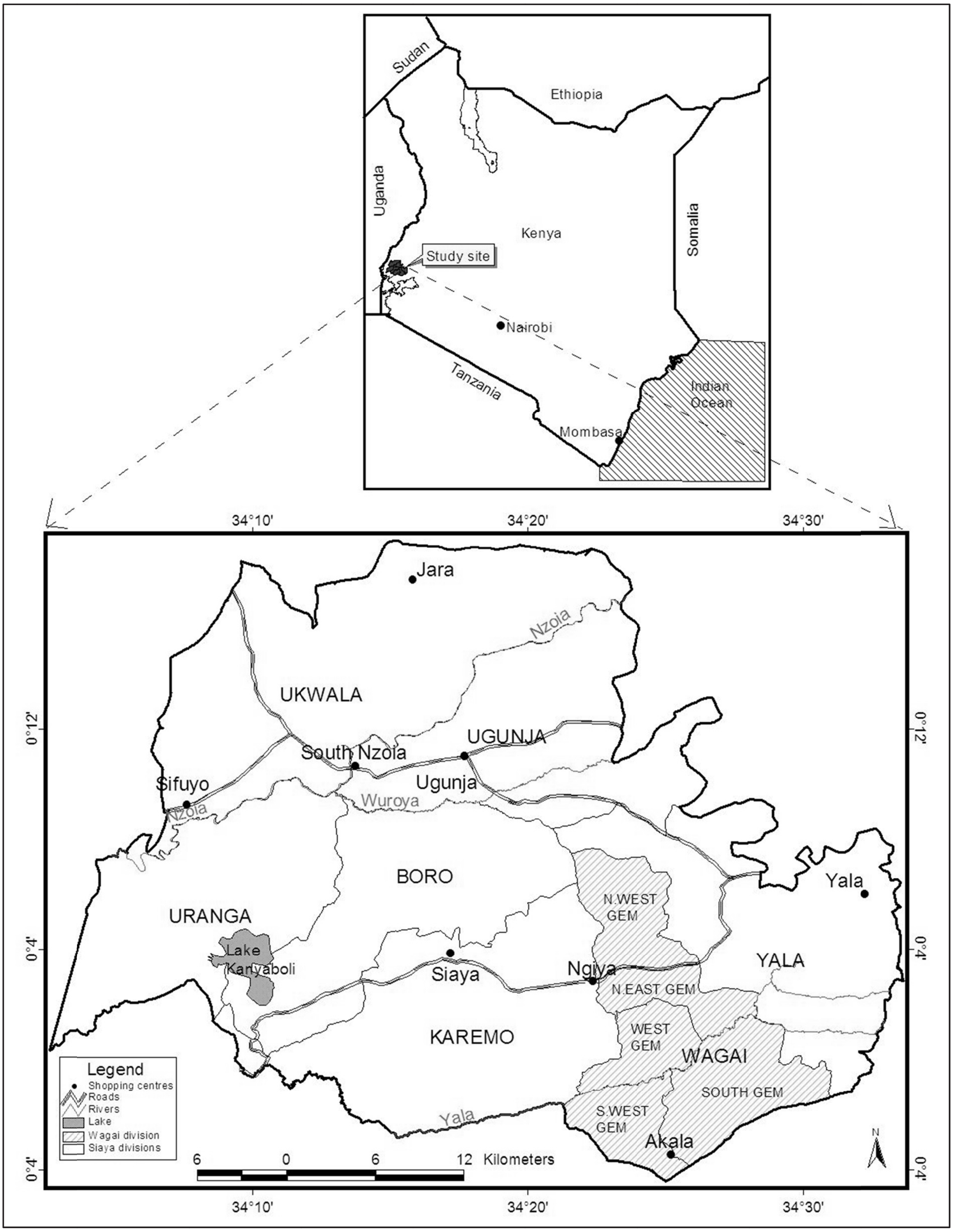
$$\frac{\partial E(y_1 / \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} k = 1,........, k \tag{6}$$

where x_k is the k^{th} component of x.

2.2 Data and Sampling Procedure

We used data collected from 326 farmers in Siaya county of western Kenya during the month of March and April 2012 through structured questionnaires. Siaya county is one of the areas where the PPT and IR maize technologies have been disseminated for the control of *Striga* weed (Figure 1). We used a multistage sampling procedure to select the sample households. In the first stage, we purposively chose Siaya county where *Striga* is most prevalent in western Kenya. In the second stage, we identified Wagai division because demonstrations and on-farm trials on the use of the two technologies had been conducted by various organizations. The third stage involved selection of sample villages and were not entirely random, since it purposively included villages where PPT and IR maize technology on-farm trials and demonstrations have been done within the five locations of Wagai division namely: North East Gem, South East Gem, West Gem, South Gem and North West Gem. In selecting the sample villages, a list of all villages where PPT and IR maize had been introduced (called PPT and IR villages) was constituted first. A total of 32 villages (17 and 15 villages in the PPT and IR maize technology sub-populations respectively) were sampled. There were no villages with both technologies. However, there were villages without any technologies which were used as control villages for matching purposes. They included 8 non-PPT and 7 non-IR villages, which were sampled randomly after compiling a list of neighbouring villages (the villages near the village from where the demonstrations and on-farm trials were carried out) within a radius of 5 to 15 km where the technology promoters had not undertaken any research activity. Fourth stage involved compiling a complete list of all households in the sampled villages where farmers were drawn randomly proportionately to the number of maize farmers in those villages.

Figure 1. Map of the study area



Source: generated from ArcGIS using georeferenced survey date (2012)

3 Results and Discussion

3.1 Descriptive Statistics

Table 1 presents the summary statistics of farm and farmer characteristics of the sampled population**.** The average age of PPT adopters and non-adopters was 50 and 40 years, respectively. On the other hand, the adopters of IR maize technology were on average aged 51 years compared to 48 years of non-adopters. The mean age difference for PPT and IR maize technology was significant at 1% level and insignificant, respectively. There was a significant difference between the number of years spent in formal schooling which was approximately 9 years for adopters of PPT and IR maize technology and 4 years for non-adopters. The average land size for PPT and IR maize technology adopters was 5.6 and 3.0 acres, respectively, while non-adopters owned 4.2 and 2.7 acres, respectively, with a significant difference at 1% and 5% respectively. The results further show that, adopters for both technologies had a higher household income compared to the non-adopters which averaged KES 53,951 and KES 44,566 for PPT and IR maize technology adopting households and KES 40,926 and KES 31,768 for non-adopters, respectively. Most of the adopters of both technologies belonged to organised farming groups (73.8% for PPT and 77.4% for IR-maize) and this has a positive attribution to adoption.

There was a significant difference between the mean access to extension services by adopters of the two technologies as reported by 79% of PPT and 66% of IR maize technology adopters. The average distance to the nearest administration centre (*DSADMN*) was 2.3 km for PPT adopters and 4.6 km for its non-adopters. On the other hand, IR maize technology adopters travelled approximately 2.4 km to the nearest administration centre compared to 4.2 km travelled by the non-adopters. The tropical livestock unit (*TLU*) is often used as a measure of wealth and reflects the importance of livestock ownership in adopting the technology. The adopters of PPT and IR maize technology owned on average 4.6 and 3.8 *TLUs*, respectively, while their respective non-adopters owned 2.2 and 3.2 units. The mean difference for PPT was significant at 1%.

3.2 Actual and Potential Adoption Rates Estimates of PPT and IR Maize Technology

Table 2 shows the estimates of PPT and IR maize technology adoption rates and their standard errors. We used variance inflation factor (VIF) to test for multicollinearity among the explanatory variables. The result was less than 10 and therefore indicative of minimum multicollinearity among the explanatory variables (MADDALA, 2001). Each ATE model was fitted separately for PPT and IR maize technology sub-samples.

Table 1. Descriptive statistics for selected farmers' and farm characteristics

Variable	Description of the variable	Measurement	PPT				IR maize technology			
			Adopters N = 61	Non-Adopters N=114	t-value	χ^2	Adopters N = 53	Non-Adopters N = 98	t-value	χ^2
			Mean/ percent	Mean/ percent			Mean/ percent	Mean/ percent		
AGEHHH	Age of the household head	Years	50 (9.3)	40 (12.4)	5.7^{***}		51 (14.9)	48 (12.1)	1.1	
YRSCHHH	Household head's years of schooling	Years	8.8 (3.7)	4.3 (3.6)	7.8^{***}		9.2 (4.6)	4.5 (3.6)	6.9^{***}	
LANDSZ	Total land size owned by a household	Acres	5.6 (2.2)	4.2 (2.3)	3.9^{***}		3.0 (2.0)	2.7 (1.6)	2.3^{**}	
LOGINCOME	Logof income	Kenya shilling	4.7 (0.4)	4.6 (0.4)	2.2^{*}		4.6 (1.2)	4.5 (0.4)	5.0^{***}	
DSADMN	Distance of the household from the nearest administration centre	Kilometres	2.3 (1.7)	4.6 (2.6)	-6.0^{***}		2.4 (2.2)	4.2 (2.9)	-4.1^{***}	
TLU	Tropical livestock unit of a household	Units	4.6 (2.5)	2.2 (2.1)	6.7^{***}		3.8 (2.9)	3.2 (2.4)	1.4	
WORKFORCE	Household's labour force	Persons	8.0 (2.4)	3.0 (1.8)	15.1^{***}		6.0 (3.6)	3.0 (1.5)	6.8^{***}	
GENDERHHH (%)	Gender of the household head	1 = Male, 0 = Female				11.7^{***}				2.5
	1 = Male		63.9	36.8			54.7	51.2		
FGMEM (%)	Whether a farmer was a group member	1 = Yes, 0 = No				19.7^{***}				39.2^{***}
	1 = Yes		73.8	38.6			77.4	24.5		
EXTENACS (%)	Whether a farmer had sought extension services	1 = Yes, 0 = No				19.6^{***}				0.6
	1 = Yes		78.7	43.9			66.0	69.4		
RADOWNSP (%)	Household head's radio ownership	1 = Yes, 0 = No				1.8				5.2^{**}
	1 = Yes		78.7	69.3			81.1	63.3		

Note: Figures in the parentheses are the standard deviations associated with the means for the variables indicated.
$^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.10$ mean significant at 1%, 5% and 10% probability levels, respectively.

Source: field survey data (2012)

The model estimates of the actual adoption rates (AAR) for PPT and IR maize technology were 36.3% and 37.0%, respectively. This shows that the adoption pattern of the two technologies are similar as the difference in the adoption rates was insignificant.

Table 2. Estimates of PPT and IR maize technology adoption rates (actual and potential) according to the attributes (covariates)

Attributes (Covariates)	ATE parametric (Probit) estimates	
	PPT	IR maize technology
	Parameter	Parameter
PPT and IR maize technology adoption rates (Probability of adopting PPT or IR maize technology):		
In the full population (ATE[1])	0.563 (0.043)***	0.460 (0.035)***
Within the PPT or IR maize technology exposed subpopulation (ATE1)	0.723 (0.030)***	0.508 (0.033)***
Within the sub-population not exposed to the PPT or IR maize technology (ATE0)	0.401 (0.065)***	0.329 (0.050)***
Actual adoption rate (AAR)	0.363 (0.015)***	0.370 (0.024)***
Estimated population adoption gap (GAP)	-0.200 (0.032)***	-0.089 (0.013)***
Expected population selection bias (PSB[2])	0.160 (0.026)***	0.048 (0.010)***

Note: Figures in the parentheses are the standard errors associated with the coefficients and marginal effects.

***P < 0.01, **P < 0.05 and *P < 0.10 mean significant at 1%, 5% and 10% probability levels, respectively.

1) ATE refers to population mean adoption outcome when all members of the population have been exposed to a technology: $A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \beta)$.

2) Population selection bias (PSB) is the difference between the population mean adoption outcome (ATE) and the mean adoption outcome among the exposed sub-population (ATE1).

Source: field survey data (2012)

The potential adoption rates (ATE), which provides indices that inform on the unmet demand for the technologies was estimated at 56.3% and 46.0% respectively for PPT and IR maize technology and this was significant at 1%. This shows that if the farmers were fully exposed, the adoption of PPT would expectedly be higher compared to that of IR maize technology. This is consistent with the findings of De Groote et al. (2010), who established that PPT had a relatively higher adoption compared to other *Striga* control strategies due to its significant net returns.

The parametric probit ATE model results show that, adoption rates of PPT and IR maize technology within the exposed sub-sample (ATE1) were 72.3% and 50.8%, respectively. This implies that PPT had a higher adoption rate within the sub-sample that was aware (exposed) of the technology, as compared to IR maize technology exposed sub-sample. The potential adoption rates within the sub-sample which was not exposed to PPT and IR maize technology (ATE0) were 40.1% and 32.9%, respectively and significant at 1%. It is worth noting that the ATE1 and ATE0 results cannot be used as true estimates of adoption rates due to biasness which arises as a result of progressive farmers usually being targeted by technology developers and promoters, or farmers self-selecting themselves into exposure (DIAGNE and DEMONT, 2007). Therefore, we used ATE for estimating potential adoption rates as suggested by DIAGNE (2006). We accounted for this expected population selection bias (PSB) by substracting the potential adoption rate (ATE) from the adoption rate within the exposed sub-sample (ATE1), hence ATE1 - ATE. In fact, the PSB for PPT was significantly higher (16%) than that of IR maize technology (4.8%), implying that had we used ATE1 as the potential adoption rates without correcting for the PSB, the results would have been biased upward by 16% and 4.8% for PPT and IR maize technology, respectively.

We further estimated the population adoption gap (GAP) as the actual adoption rate minus potential adoption rate (AAR - ATE) separately for each of the technologies. The difference gives the adoption gap for both technologies or the unmet demand if the population from which the sub-samples were drawn, were to be exposed. The adoption gap for PPT and IR maize technology was 20.0% and 8.9% respectively (Table 2). These values can be interpreted to mean that, were it that the whole population was exposed to PPT, then by the end of 2012, the adoption rate could have been 56.3% instead of 36.3%, and that a complete population exposure to IR maize technology could have led to 46.0% adoption instead of what was observed during the study (37%). Continous exposure of both technologies is therefore likely to enhance adoption.

3.3 The Determinants of the Probability of Exposure and Adoption of PPT and IR Maize Technology

Table 3 shows the marginal effects of the determinants of PPT and IR maize technology exposure and adoption. Farmers who were members of producer groups had a higher probability of being exposed to PPT (ME = 0.192). However, in this study we found no significant influence of farmer group membership on the probability of being exposed to IR maize technology. On the other hand, the marginal effects for farmer group membership (*FGMEM*) on adoption of PPT (ME = 0.307) and IR maize technology (ME = 0.540) were positive, implying that farmers who were members of a group had a higher probability of adopting PPT and IR maize technology. This is consistent to a *priori* expectations that farmers in groups have a higher probability of adopting new technologies due to the accrued benefits especially sharing of ideas. This finding shows the critical importance of membership in farmer groups in the process of new technology adoption (see Table 1). This has been attributed to lower transaction and transformation costs related to information searching as well as in accessing other inputs related to technology adoption (AMUDAVI et al., 2008; SHIFERAW et al., 2009). Collective action is one of the effective ways of overcoming high transaction costs by smallholder farmers (KHERALLAH and KIRSTEN, 2001). GROOTAERT (2001) argues that, social capital which are the networks, values and norms that govern interactions among people are crucial in reducing the transaction costs incurred by farmers. However, a study by MURAGE et al. (2011) contradicts these findings by arguing that, farmers who belonged to organized groups were likely to take longer time to adopt PPT than non-members, a fact that was ascribed to possible negative attitudes derived from the groups.

The probability of older farmers getting exposed and adopting PPT was higher compared to their younger counterparts. This could be due to their enormous farming experience acquired overtime. This was inconsistent to the findings of ADESINA and BAIDU-FORSON (1995) and RAHELIZATOVO and GILLESPIE (2004) who observed that older farmers are less risk takers (risk averse) than younger farmers, and therefore had less likelihood of being exposed to new technologies. Age was, however, insignificant on the exposure and adoption of IR maize technology. The descriptive statictics shows a significant difference between the age of the adopters and non-adopters from the PPT sub-population. However, it was insignificant on IR maize technology (Table 1).

The probability of educated farmers being exposed to IR maize technology (ME = 0.016) and eventually adopting the technology was higher compared to their less educated farmers. This is more likely as a result of the fact that, more educated farmers are more able to effectively search and interpret technology information (ZHANG et al., 2010). The positive influence of education on technology adoption was consistent to findings from other studies (e.g. ALENE et al., 2000; MWABU et al., 2006; OUMA and DE GROOTE, 2011). In a related study, SALASYA et al. (2007) established that educated farmers were more likely to adopt IR maize technology in western Kenya. The variable had no significant influence on PPT exposure and adoption. This could be attributed to the fact that information on PPT has mostly been disseminated through pathways such as farmer teachers (FT), farmer field schools (FFS) and field days (FD) which utilize the social networks of the community (MURAGE et al., 2012). These pathways ensure that, information is relayed to farmers through local language easily understood by less educated farmers. Therefore, they are equally likely to adopt the technology compared to the educated farmers.

Table 3. Marginal effects of estimated parametric models for PPT and IR maize technology exposure and adoption

Variable	Variable definition	PPT			IR maize technology		
		Exposure Probit model	ATE Probit adoption model	Classic Probit joint exposure and adoption model	Exposure Probit model	ATE Probit adoption model	Classic Probit joint exposure and adoption model
		Marginal effects (dy/dx)	Marginal effects (dy/dx)	Marginal effects (dy/dx)	Marginal effects (dy/dx)	Marginal effects (dy/dx)	Marginal effects (dy/dx)
AGEHHH	Age of the household head	0.015^{***}	0.020^{***}	0.006^{*}	0.001	-0.003	-0.005
GENDERHHH	Gender of the household head	-0.028	0.433^{***}	0.198^{**}	0.224^{***}	-0.207^{*}	-0.068
HHSIZE	Household size	0.035^{**}	0.100^{***}	0.059^{***}	0.035^{**}	-0.019	-0.006
EXTENACS	Whether a farmer had sought extension services	0.202^{*}	-0.145	0.084	0.083	0.042	0.057
RADOWNSP	Household head's radio ownership	-0.076	0.046	-0.109	0.128	0.101	0.112
FGMEM	Whether a farmer was a group member	0.192^{*}	0.307^{*}	0.214^{**}	0.027	0.540^{***}	0.414^{***}
YRSCHHH	Household head's years of schooling	0.024	-0.003	0.013	0.016^{*}	0.045^{***}	0.043^{***}
DSADMN	Distance of the household from the nearest administration centre	-0.124^{***}	-0.103^{**}	-0.161^{***}	-0.020	-0.078^{***}	-0.075^{***}
LOGINCOME	Logof income	0.174^{**}	-0.011	-0.034	0.042	-0.021	-0.035
TLU	Tropical livestock unit of a household	0.028	0.070^{**}	0.043^{**}	-0.005	-0.011	-0.002
LANDSZ	Total land size owned by a household		0.064^{**}	0.010		0.022	-0.000
Constant		-4.179^{***}			-1.806		
N		175			151		
Wald chi2(11)		121.40	34.11	75.89	32.85	44.87	52.52
Prob> chi2		0.0000	0.0003	0.0000	0.0003	0.0000	0.0000
Pseudo R^2		0.5004			0.1860		

$^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.10$ mean significant at 1%, 5% and 10% probability levels, respectively.

Source: field survey data (2012)

Distance to the nearest administration centre had a negative marginal effect (ME = -0.124) on the probability of household exposure to PPT, implying less probability of exposure for households located away from the agricultural offices. The marginal effects were also negative (ME = -0.103, ME = -0.078) for the influence of distance to adoption of PPT and IR maize technology, respectively. This inverse relationship implies that, as the distance increases, there is possible increase in transaction and transformation costs and therefore reduces the possibility of farmers adopting new technologies. It was similarly reported in DORWARD et al. (2005) that poor infrastructure linking farmers to the input and output markets leads to high transaction costs, which could hinder the adoption of new technologies being promoted.

Male headed households were more likely to adopt PPT (ME = 0.433), while female headed households had a higher probability of adopting IR maize technology (ME = -0.207). This is consistent with the findings by KALIBA et al. (2000), DIAGNE (2009) and YESUF and BLUFFSTONE (2009) and yet contrary to those by KHAN et al. (2008b), who indicated that female headed households were more likely to adopt PPT. The difference could be ascribed to the fact that, more male headed households are probably taking up PPT attributed to increased income levels attained by the adopting female headed households.

There was a significant positive relationship between household size (*HHSIZE*) and exposure (ME = 0.035), and adoption (ME = 0.100) of PPT. The probability of higher exposure and adoption by large households would be attributed to the diverse avenues from which household members can access and share information and ideas. Furthermore, large sized households are likely to provide a larger pool from which to draw family labour especially if the technology is labour intensive as is the case with PPT. These results corroborate those of AMUDAVI et al. (2008) who found a positive and significant relationship between PPT expansion and household size in western Kenya. However, the variable had no significant influence on IR maize technology adoption.

The marginal effect for *TLU* was positive and significant (ME = 0.070) for PPT, implying a probable increase in adoption of PPT with every unit increase in *TLU*. As noted earlier, *TLU* is often used as a proxy for household wealth and therefore it is more likely to lead to technology adoption especially for capital intensive technologies. Consistent to this notion, SALASYA et al. (2007) found that livestock ownership in western Kenya positively influenced the decision to adopt a stress-tolerant maize hybrid (WH 502). Similarly, SIMTOWE et al. (2011) report a positive relationship between livestock ownership and adoption of improved pigeon pea technologies in Tanzania. Elsewhere, the positive relationship is attributed to the need for livestock fodder which is an accrued benefit from adoption of PPT. Therefore, farmers who owned more livestock were more likey to adopt PPT in order to benefit from the livestock fodder available from the companion crops planted under PPT e.g. Napier grass and *desmodium* (KHAN and PICKETT, 2004).

Farmers who had higher income levels (*LOGINCOME*) were more likely to be exposed to PPT (ME = 0.174). This is consistent with the findings by ALENE et al. (2000) who established that wealthier farmers had a higher probability of adopting improved maize technologies, compared to the less income households.

4 Conclusions and Implications

This study sort to establish the comparative advantage of adopting PPT or IR maize technology by smallholder farmers, considering that: (a) both technologies are aimed at controlling *Striga*, and (b) once developed and ready for use by farmers, scaling-out of these technologies have a social cost, and therefore highlighting the best-bet option from the farmers' perspective. In particular, the objective was to determine which of the two technologies has the highest adoption potential, contingent on farmer resources and socio-economic factors, so as to ensure optimal allocation of limited agricultural production resources. Using exposure as a treatment variable, the study estimated the actual and potential adoption rates of PPT and IR maize technology within the ATE analytical framework.

The study showed that, distance to the nearest administration centre and adoption of PPT are negatively correlated, meaning that, farmers that are distant from major administration centres are less likely to proportionately adopt more of PPT. These implies the need for increased access to urban centres through investments in road and transport infrastructures for better scaling-out of the PPT. Moreover, since PPT had a higher potential adoption rate as compared to IR maize technology and given that the two technologies target *Striga* weed control, it would seem that PPT needs to be more prioritized for dissemination if the technology developers put extra efforts to bridge the adoption gap. The results further show that, farmer groups matter in the adoption of new technologies, which implies the need to encourage and facilitate the formation of more of such groups that would then act as a platform for faster technology adoption.

The study revealed that exposure to both PPT and IR maize technology are not gender neutral: women were more exposed to IR maize technology than men, while the converse was true with PPT. It is unclear why this is the case, which means that further studies would be necessary to exhaustively explain this dichotomy. Furthermore, the more educated a farmhold head is, the more likely IR maize technology is adopted. Whereas, PPT is knowledge intensive in implementation, the IR maize technology requires more knowledge in handling – the chemical seed coating can be hazardous to health. The requisite education stock is thus more intense than that associated with PPT. This, therefore, suggests that, IR maize technology is more appropriate for relatively well educated households, if only to cater for the hazardous nature of the seed coated chemical.

The study showed increased exposure of PPT dissemination to well-off famers, as measured by the level of income. This should be a major concern since it suggests that, poorer farmers seem to be relegated in so far as exposure to the requisite information for technology uptake, and yet these are the farmers who need the information most. Effective measures geared towards improved access to information by this segment of famers would go along way in addressing the *Striga* weed menace, whether it is through PPT or IR maize technology adoption. The results further indicated a positive correlation between livestock ownership and adoption of PPT. This implies the need to target farmers who own livestock due to the accrued benefit of fodder.

Generally, although differences in the adoption rates of the two technologies may result from unobservable village characteristics that would not have been accounted for in the study design, the applied method showed good matching results leading us to believe that the findings are valid. Furthermore, the gaps from the study results suggest a need for further research on the impact of adopting PPT and IR maize technology on maize productivity particularly within the context of cost effectiveness and adoption sustainability.

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