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Full Length Research Paper

Determinants of adopting imazapyr-resistant maize for *Striga* control in Western Kenya: A double-hurdle approach

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Discussions and debates have been on going about *Striga*, a major constraint to increasing maize production and food security in western Kenya. To inform these debates this paper applies econometrics to farm survey data in order to estimate and determine the factors which drive farmers' decision to adopt imazapyr-resistant maize (IRM), a novel technology for *Striga* control. The study uses data from a multistage, random sample of 600 households of which, 169 were IRM adopters and 431 were non-adopters. This paper tests the hypothesis that the factors affecting farmers' decision to adopt IRM are not necessarily the same as those affecting their extent of adoption. Results from the double-hurdle model indicates that age of the household head, household size, membership to social group, access to extension services and perception towards IRM for *Striga* control were found to influence the decision to adopt IRM. And, household size, gap between maize production and consumption per capita, access to extension services and perception towards IRM for *Striga* control influenced the extent the farmer is willing to adopt. The paper concludes with policy implications aimed at renewing the focus on IRM transfer in western Kenya and other areas with similar conditions.

Key words: Adoption, double-hurdle model, imazapyr-resistant maize (IRM) technology, *Striga*, Kenya.

INTRODUCTION

Since mid-seventies *Striga* has entered Africa (Klingman, 1961), there is increasing evidence now that *Striga* is a main constraint in increased food production, food security and poverty reduction in western Kenya (De Groote et al., 2007; Kanampiu et al., 2006; Manyong et al., 2008; Woomer and Savala, 2008). After several years, discussions and debates are still going on about many issues regarding *Striga* such as: the severity and incidence of the disease, the magnitude of its economic losses, clear mechanisms of spreading and the new approaches for its control to overcome this nightmare.

There is no doubt that a strategic decision should be made to fight *Striga* in order to attain self-sufficiency in maize grains and increase food security. Despite the introduction of various technologies, traditional and novel ones such as push-pull to farmers, *Striga* continues to expand and the appropriate techniques and strategies to contain *Striga* epidemic deemed as failed. The parasite competes with its host for resources; changes host plant architecture and reduce the photosynthetic rate and the water use efficiency of the host (Van Ast et al., 2000; Watling and Press, 2001). This has led to the emergence of a new technology known as imazapyr-resistant maize (IRM) which has proven to be efficient for *Striga* control (Kanampiu et al., 2006; De Groote et al., 2006). The International Maize and Wheat Improvement Center (CIMMYT), Badische Anlin and Soda Fabrik (BASF), African Agricultural Technology Foundation (AATF) and other stakeholders have made efforts in bringing IRM technology to farmers as assistance for *Striga* control. IRM technology utilizes herbicide resistant maize seed

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coated with the herbicide imazapyr. The herbicide used is derived from a naturally occurring gene in maize originally identified by BASF and made available to CIMMYT. The technology has been introduced to a large scale since 2004 after field trials and tests organized for farmers in 2002 and 2004. However and surprisingly, only 28% of the sampled households in western Kenya adopted it (Mignouna et al., 2011) and the reasons for this low adoption are unclear. Therefore, there is a need to better understand why before the introduction of any further new agricultural technology.

Several adoption studies concentrate on cross-sectional analysis of the determinants of agricultural adoption at the farm level. For instance, the CIMMYT studies in Kenya and other East African countries (Mwangi et al., 1998; Doss, 2003) examined adoption decision processes for maize seed and fertilizer technologies and showed that farmer characteristics such as age, gender, and wealth are keys to adoption decisions. For Ouma et al. (2002), they found agro-ecological differences, gender, manure use, hiring of labour and extension are important to adoption of fertilizer and hybrid seed on maize production in Embu district. Suri (2011) showed that technology profitability, farmers' training as well as observed and unobserved differences among farmers and across farming systems are the major determinants affecting maize technology adoption in Kenya. According to the study done by Jayne et al. (2006), the national-level, region-specific, and household specific factors are associated with smallholders' use of improved maize technologies in Kenya. Mwabu et al. (2006) in their research on the adoption of improved maize varieties and their impact on poverty in Laikipia and Suba districts found that the price of maize, education level, and distance to the roads are the main determinants of hybrid maize adoption by farmers.

To inform these debates, this paper aims to support the decision of adopting IRM as a practical answer to the *Striga* crisis and applies econometrics to farm survey data in order to estimate and determine the factors affecting farmers' decision to adopt IRM technology in western Kenya. This paper tests the hypothesis that factors affecting farmers' decision of adopting IRM are not necessarily the same factors affecting their extent of adoption.

METHODS

Study area

Nyanza and Western provinces in the Lake Victoria zone in western Kenya were chosen for this study based on the importance of maize as a major food and cash crop for small-scale farmers in the region and of *Striga,* which constitutes the most important biological constraint to the maize production (Manyong et al., 2008). Soil fertility decline is a major problem in the area as a result of continuous cropping with little use of inputs. Furthermore, the mean annual rainfall which ranges from less than 1000 mm near the shores of Lake Victoria to 2000 mm away from the lakeshore is suitable to *Striga* as it grows well in areas receiving less than 1500 mm rainfall per annum (Oswald, 2005). This explains partially the severe infestation of *Striga* (*Striga hermonthica*), a parasitic weed that substantially reduces maize yield in the region.

Study design and data

The household survey was carried out between September and December, 2008. A structured survey questionnaire was prepared and trained enumerators collected the information from households via personal interviews. A multistage, random sampling procedure was adopted to get the total sample size of 600 households comprising 169 adopters and 431 non-adopters of IRM from Nyanza, and Western provinces of western Kenya. First, two provinces and six districts were selected regarding the importance of maize production and level of *Striga* infestation. Second, 100 farmers were randomly selected from each district and stratified into two, namely adopters of IRM and non-adopters. Adopters were identified by using the list made available by the front-line extension workers and farmers assisted in confirming it. The data collected valuable information on several variables including socio-economic, farm-related, institutional and technological factors. The technology-adoption decision of a household is assumed to be motivated by utility maximization.

Theoretical model and empirical specifications

Adoption is conventionally conceptualized to be the mental process through which an individual passes from first learning about an agricultural innovation to final adoption (Mutandwa et al., 2007). Adoption is seen as the decision by an individual to become a regular user of the new idea (Kotler and Armstrong, 1994). Authors argue that adoption of a new technological innovation is underpinned by its underlying attributes or consists of inter-related stages (Batz et al., 1999; Fernandez-Cornejo et al., 2002; Rogers, 2003).

In modeling the utility or satisfaction derived from the use and integration of IRM into the smallholder farming system, the economic values or benefits associated with traditional maize varieties such as local maize and systems with the novel variety IRM need to be considered. A typical smallholder-farming household seeks to maximize a multi-dimensional objective function, including increasing incomes and food security, and reduction of all forms of risk (Strauss et al., 1989). When there is a change in economic parameters associated to IRM technology, the central question is related to how much compensation, whether paid or received, would make the decision maker indifferent about the change. Thus the change in welfare associated with this development was used as the basis for economic valuation process. When an individual farmer faces a change in a measurable attribute, for example higher control for *Striga* from new IRM variety (q), then q changes from q_0 to q_1 (with $q_1 > q_0$). The indirect utility function u after the change becomes higher than the status quo. Now the status quo can be represented econometrically as follows:

$$u_{1j} = u_i\,(y_i, z_j, q^{\circ}, \varepsilon_{0j})$$

On the other hand, the changed or final state due to the introduction of IRM is shown by:

$$u_{2j} = u_i\,(y_i, z_j, q^1, \varepsilon_{ij})$$

Where, y_i, refers to the farmer's income, Z_j is a vector of the farmer's socio-economic variables and attributes of choice, and ε_j is the stochastic error term representing other unobserved utility components,

The farmer would opt, pay and adopt IRM if the following condition holds:

$$u_i\,(y_i - P_i, z_j, \varepsilon_{ij}) > u_0\,(y_i, z_j, \varepsilon_{0j})$$

Where: P_i is the monetary investment associated with the new variety.

Since the random components of the preferences are not known with certainty; it is only possible to make probabilistic statements about expected outcomes. Thus, the decision by the farmer to adopt IRM is the probability that he/she will be better off if this variety is used. This is represented as follows:

$$Prob\ (Yes_i) = Prob\ [u_i\ (y_i - P_i, z_j, \varepsilon_{ij}) > u_0\ (y_i, z_j, \varepsilon_{ij})]$$

Since the afore-mentioned utility functions are expressed generally, it becomes critical to specify the utility function as additively separable in deterministic and stochastic preferences. Using, this argument, the function becomes:

$$u_i\ (y_i, z_j, \varepsilon_{ij}) = u_i\ (y_i, z_j) + \varepsilon_{ij}$$

Where: The first part of the right hand side is the deterministic part and the second part is the stochastic part. The assumptions that ε_{ij} are independently and identically distributed with mean zero describes most widely used distributions.

Two widely used distributions are the normal (probit) and logistic regression models. In this study, the statistical dichotomous choice data is modeled by superimposing a probability function. The dependent variable takes the value 1 if the smallholder-farming households are willing to adopt IRM or 0 if they are not willing to adopt. And if the farming households adopt, how much could they adopt? The observed adoption of IRM is hypothesized to be the end result of combined effects of a number of factors related to the farmer's goals and means of achieving them.

Several hypotheses can be derived from these two sets of decision; factors that affect adoption and factors that affect intensity of IRM. The following variables in the models were hypothesized to influence the adoption of IRM in different directions. External influences include institutional support systems such as marketing facilities, credit and extension services which are important in affecting adoption (Feder, 1980). Credit was not included as factor influencing the IRM adoption because very few households in the study area used credit to purchase farm inputs. Also access of the introduced IRM was not included as determinant explaining adoption because access of the novel technology in the study area was mainly done through extension services and farmer's social groups which were already hypothesized to influence IRM adoption. Farmer's age may influence both the decision to adopt and extent of adoption of IRM. It may be that older farmers are more risk averse and less likely to be flexible than younger farmers and thus could have a lesser likelihood of adopting new technologies. However, it could also be that older farmers have gained over time farming knowledge and experience and could be better able in evaluating technology information than younger farmers, and hence could have a higher probability of adopting the practice (Feder et al., 1985; Belknap and Saupe, 1988). For the gender of the household head the assumption made was that the head of the household is the primary decision maker and gender difference could be found to be one of the factors influencing the adoption of new technologies. Due to many socio-cultural values and norms, males have more access and control over vital production resources such as land, information, credit and labour than women (Njeri, 2007). Therefore, it was hypothesized that gender could be related to the adoption of IRM package. Education level of the household head increases farmer's ability to obtain, process, and use information relevant to the adoption of IRM. Thus educated farmers have been found to be more likely to adopt innovations (Nkamleu and Adesina, 2000; Asfaw and Admassie, 2004). Thus it is hypothesized that farmers with more education could be more likely to adopt IRM than farmers with less education depending also on the education level (that is, primary, junior and secondary levels of education). Household size, a proxy to labour availability can be an incentive to produce more to meet the needs hence looks for high-yielding varieties in the *Striga* environment. Therefore a positive relationship was hypothesized between IRM package and household size is the major source of labour for farm activities (Adesina et al., 2000). Large households have the capacity to relax the labour constraints required during the introduction of new technologies (Ayuya et al., 2011). It is expected that a larger household size could affect the decision of adopting IRM. Farm size is hypothesized in a way that those producers with more land could be more likely to increase the intensity of adoption. Having a large land contributes to perceived security and increased willingness to invest in new technology (Caveness and Kurtz, 1993). As a result, positive relationship was hypothesized between farm size and IRM adoption. Gap between maize production and consumption per capita is hypothesized to be a stimulant of IRM adoption. The difference between maize production and consumption per capita which can result into deficit can stimulate the demand for high-yielding varieties. Belonging to a rural social group enhances social capital allowing trust, idea and information exchange. Better social relations and communication among farmers are crucial for technology adoption and diffusion. Thus membership to a group could increase the technology adoption. Access to extension services is hypothesized to relate to adoption by exposing farmers to new information and technical skills about *Striga* control. Perception of the farmer towards IRM for *Striga* control is critical in the adoption decision (Dolisca et al., 2006) in motivating farmers. Farmers who perceived IRM as being consistent with their needs and compatible to their environment were expected to adopt it since they find it as a positive investment. Perception towards IRM is hypothesized to be positively related to the adoption decision.

Econometric specification: The double-hurdle model

While other studies have approached a similar problem using the logistic analysis (Kavia et al., 2007), Heckman procedure (Nkonya et al., 1998; Adeoti, 2009); this paper compares the results from a joint Tobit and a Double-Hurdle (DH) models because we believe that factors that affect farmers' choice of an option should not necessarily be the same as those that affect the intensity of use. This is because the decision to choose a particular maize option is obviously associated with some threshold effects. In terms of policy relevance, our analysis clearly shows that adoption and intensity may be different decisions and that estimation of intensity on the basis of factors affecting adoption, as implied by other approaches, may be liable to error.

The DH model, originally proposed by Cragg (1971) has been extensively applied in several studies (Martínez-Espiñeira, 2006; Moffatt, 2003; Newman et al., 2001; Burton et al., 1996). However, it has not been much used in the area of adoption of agricultural technologies; an exception would be Berhanu and Swinton (2003). Double-hurdle model was used in this case to determine the factors that influence the decision to adopt and the extent of adoption of IRM in order to identify areas of intervention. The underlying assumption in the DH approach is that farmers make two decisions with regard to their decision to grow IRM. The first decision is whether they will grow IRM. The second decision is about the amount of land that they will allocate, conditional on the first decision. The two decisions are, therefore, whether to grow IRM and how much to grow. The importance of treating the two decisions independently lies in the fact that factors that affect one's decision to adopt may be different from those that affect the decision on how much to adopt. This implies that households must cross two hurdles in order to adopt. The first hurdle needs to be crossed in order to be a potential adopter. Given that the households is a potential adopter, their current circumstances then dictate whether or not they do in fact adopt: this is the second hurdle (Moffatt, 2003). The DH model allows for the possibility that these two decisions are affected by a different set of variables. The advantage with this approach is that it allows us to understand characteristics of a class of households that would never adopt IRM. Thus the probability of a household to belong to a particular class depends on a set of household characteristics. The DH model is a parametric generalization of the Tobit model, in which two separate stochastic processes determine the decision to adopt and the level of adoption of technology. The first equation in the DH model relates to the decision to adopt (y) can be expressed as follows:

$y_i = 1$ if $y_i^* > 0$ and 0 if $y_i^* \leq 0$ (1)

$$y_i^* = x_i'\alpha + \varepsilon_i$$

Where: y^* is latent adoption variable that takes the value of 1 if a household grew IRM and 0 otherwise, x is a vector of household characteristics and α is a vector of parameters.

The second hurdle, which closely resembles the Tobit model, is expressed as:

$t_i = t_i^* > 0$ and $y_i^* > 0$

$t_i = 0$ otherwise

$$t_i^* = z_i'\beta + u_i \qquad (2)$$

Where: t_i is the observed response on how much land one allocated to IRM, z is a vector of the household characteristics and β is a vector of parameters.

The decision of whether or not to adopt IRM and about how much land to allocate to IRM can be jointly modelled, if they are made simultaneously by the household; independently, if they are made separately; or sequentially, if one is made first and affects the other one as in the dominance model (Martínez-Espiñeira, 2006). If the independence model applies, the error terms are distributed as follows:

$\varepsilon_i \sim N(0, 1)$ and $u_i \sim N(0,\delta^2)$.

If both decisions are made jointly (the Dependent DH) the error term can be defined as:

$(\varepsilon_i\ u_i) \sim BV\,N(0,Y)$

Where $Y = \begin{bmatrix} 1 & \rho\delta \\ \rho\delta & \delta^2 \end{bmatrix}$

The model is said to be a dependent model if there is a relationship between the decision to adopt and the intensity of adoption. This relationship can be expressed as follows:

$$\rho = \frac{\operatorname{cov}(\varepsilon_i u_i)}{\sqrt{\operatorname{var}(\varepsilon_i)\operatorname{var}(u_i)}}$$

If $\rho = 0$ and there is dominance (the zeros are only associated to non-participation, not standard corner solutions) then the model decomposes into a Probit for participation and standard OLS for Y.

Following Smith (2003) we assume that the error terms and ε_i and u_i are independently and normally distributed and thus we have the following expression:

$$\begin{pmatrix} \varepsilon_i \\ u_i \end{pmatrix} N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \delta^2 \end{pmatrix}\right]$$

And finally, the observed variable in a DH model is $t_i = y_i t_i^*$ and the log-likelihood function for the DH model is:

$$LogL = \sum_0 \ln\left[1 - \Phi(x_i'\alpha)\Phi\left(\frac{z_i'\beta}{\delta}\right)\right] + \sum_+ \ln\left[\Phi(z_i'\alpha)\frac{1}{\delta}\phi\left(\frac{y_i - x_i'\beta}{\delta}\right)\right]$$

Where: $\Phi(\cdot)$ refer to the standard normal probability and $\phi(\cdot)$ refer to density functions.

Thus in this study we estimate the decision to adopt and the extent of adoption using a DH model.

RESULTS AND DISCUSSION

Descriptive statistics

Table 1 presents the t-test and chi-square comparison of means of selected variables by adoption status for the surveyed households. Some of these characteristics are the explanatory variables of the estimated models we present further on. The dataset contains 600 farm households and of these, about 28% were adopters, that is, planted at least a unit of square meter of IRM during 2007/08 cropping season. The area planted of IRM is about 0.23 ha for adopters. The analysis of the data shows that there is a significant (P < 0.01) mean difference between age of adopters and non-adopters. Average age of sample household head is about 49 years with non-adopters. No significant difference is observable in the gender of the household head although the groups vary significantly in terms of their education level. Primary and junior levels of education (1 to 8 years) are lower for adopters however adopters have higher proportion of household heads with secondary education. This suggests that education might be correlated with decision to adopt. The household size is 6.22 persons for adopters and 5.28 for non-adopters and the difference is statistically significant suggesting the importance of family size for adoption of new technologies. No significant difference is observable in total farm size and gap between maize production and consumption per

Table 1. Descriptive summary of variables used in estimations (N = 600).

Variable	Unit	Adopters (N=169)	Non-adopters (N=431)	t-stat (chi-square)
Dependent variable				
Area planted of IRM	Ha	0.23	0.00	0.23***
Adoption	1/0	1.00	0.00	-
Independent variable				
Age of the HHH	Years	48.92	45.19	3.73***
Gender of HHH (male=1)	1/0	0.71	0.75	-0.04
HHH education 1-4 years (yes=1)	1/0	0.09	0.27	-0.17***
HHH education 5-8 years (yes=1)	1/0	0.36	0.48	-0.12***
HHH education greater than 8 years (yes=1)	1/0	0.54	0.25	0.29***
HH size	Count	6.22	5.28	0.94***
Farm size	Ha	0.85	0.41	0.44
Gap between maize production and consumption per capita	Kg	-116.66	8.21	-124.87
Membership to social group (yes-1)	1/0	0.75	0.58	0.17***
Access to extension services (yes=1)	1/0	0.70	0.39	0.32***
Perception towards IRM for *Striga* control	1/0	0.96	0.72	0.25***

Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels; HHH= household head.

capita. There is significant difference in terms of household membership in different rural institutions. The result also depicts that the adopter categories are distinguishable in terms of their access to extension services and perception towards IRM for *Striga* control. This simple comparison of the two groups of smallholders suggests that adopters and non-adopters differ signifycantly in some proxies of socio-economic characteristics.

Econometric results

All parameter estimates of the models were generated using Stata version 11 (StataCorp, 2009) and the results from the study showed that the coefficients of most of the variables hypothesized to influence the decision and extent of adoption of IRM have the expected signs. The Probit results on the decision to adopt IRM and truncated regression analysis results on the extent of adoption are presented in Table 2.

Determinants of IRM adoption

To identify the factors influencing the decision to adopt IRM, the Probit model was estimated (first hurdle). The results shown in Table 2 reveal that five factors are significant in influencing farmers' decision to adopt IRM of whose four at 1% namely: age of household head, household size, access to extension services and perception towards IRM for *Striga* control. Membership to any rural association is significant at 5%. The log likelihood for the fitted model was -231.29402 and the $\chi 2$ value of 232.48 indicates that all parameters are jointly significant at 5%. Age has been found to have a positive relationship with the decision to adopt IRM technology implying that old farmers are more willing to adopt IRM than young farmers as a result of age based knowledge gained and probably experiences accumulated over years' differences. However these results were inconsistent with those of Langyintuo and Mulugetta (2005), Rahelizatovo and Gillespie (2004), Barham et al. (2004), and Baidu-Forson (1999), who argued before that younger farmers are more receptive towards newly introduced technologies than older farmers. The effect of household size was found to be positive and significant suggesting that the larger in number of persons in the household the more likely the farmer is willing to accept high-yielding variety in *Striga* infestation environment. The interpretation for this is that the bigger the household size the more the farmer flexibility in their decision making certainly due to availability of more labour to use on the new practices. Similar results were found by Amsalu and Jan de (2007) who stated that the household size had a significant and positive effect on determinants of adoption and continued use of stone terraces for soil and water conservation in an Ethiopian highland watershed. Membership to a social group which assessed whether the farmer or household is part of a community organization or cooperative was found to be positively and significantly associated with a higher probability of adopting IRM. This agrees with Walton et al. (1969) that the most important issue in adopting a new technology is group unity. Such unity is attributed to a spirit of teamwork

Table 2. Maximum likelihood estimates for the joint Tobit and Hurdle models.

Model specification	Joint	Double-hurdle	
	Tobit	Probit	Truncated
Dependent variable	**Area planted of IRM**	**Dummy = 1 if IRM adopted**	**Area planted of IRM**
Variable	**Coefficient**	**Coefficient**	**Coefficient**
Age of the HHH	0.0129***	0.0635***	0.0005
Gender of HHH (male=1)	-0.0741**	-0.2380	-0.0120
HHH education 1-4 years (yes=1)	-0.1118	-0.9284	0.2132
HHH education 5-8 years (yes=1)	0.1361	0.1802	0.2366
HHH education greater than 8 years (yes=1)	0.4140**	1.5767	0.2544
HH size	0.0377***	0.0901***	0.0380***
Farm size	-0.0010	-0.0052	0.0160
Gap between maize production and consumption per capita	0.0001***	0.0000	0.0002***
Membership to social group (yes-1)	0.0769**	0.3545**	0.0035
Access to extension services (yes=1)	0.1017***	0.4486***	0.0602***
Perception towards IRM for *Striga* control	0.2715***	1.3262***	-0.0908**
Constant	-1.4336***	-6.0134***	-0.2328
Model summary			
Number of observations	573	573	169
Log-likelihood	-141.54089	-231.29402	196.83067
LR chi2(11),Wald chi2 (11)	233.21	232.48	364.27
Prob > chi2	0.0000	0.0000	0.0000
AIC (-LOG-L + k/N)	0.27		-1.09
LR test for Tobit vs. Truncated regression			214.16 (0.0000)

*, **, *** Coefficients are significantly different from zero at the 99% (***), 95% (**) and 90% (*) confidence levels, respectively.

and cooperation where there is communication. Membership to a group may enable farmers to learn about a technology via other farmers and from other development agencies (Nkamleu, 2007). Information flow between members of farmer groups is usually very rapid and important. Farmer groups give their members a wider opportunity for educating each other. Higher interactions among members of a group increase chances to widen understanding of new technologies and their advantages.

These results underscore the importance of social capital in accessing new technologies by the poor smallholder farmers. Access to extension services was found positively significant, which implies that the contact with an extension agent is necessary to enhance the rate of adoption. As extension services popularize the innovation by providing necessary information, appropriate knowledge and special skills, they enable farmers to apply innovation. Majority of the farmers in western Kenya have not been able to obtain technological information due to lack of know-how, access to communication media and technical training. This finding is in conformity with other studies (Abebaw and belay, 2001). Likewise Adesina et al. (2000) found that the probability of adoption is also higher for farmers organized in groups. The decision to adopt is also influenced by farmers subjective perceptions of the characteristics of new agricultural technologies as found Adesina and Baidu-Forson (1995). Perception towards IRM for *Striga* control is positively and significantly associated with a great likelihood of adopting IRM having in mind the yield performance that will be generated from IRM. Positive perception increases the probability of adoption (Ostlund, 1974). Farmers who perceived the technology as beneficial to them would adopt it more than those whose perception is negative or indifferent.

Determinants of extent of adoption

The estimated results for DH and Tobit models on adoption of IRM in western Kenya are presented in Table 2. The Tobit model results have been presented for comparison. The results from the two models were comparable which show the robustness of our results to model specification. All the statistically significant variables except the perception towards the technology for *Striga* control had the same directional effects in all of the two models. The likelihood ratio test statistic specified in Table 2 favoured the DH model over the Tobit. The Akaike Information Criterion (AIC) estimates also confirmed the same model as a better fit for the data. Henceforth, we shall base our discussion on the results from the DH model. Four variables were found to have significant effects in explaining the level of adoption of IRM by households, measured in term of area planted under IRM. These included household size, gap between maize production and consumption per capita, access to extension services and perception towards IRM for *Striga* control.

As argued by Asfaw et al. (2010) awareness in technology transfer is very important. In most of the adoption cases in developing countries, adoption is hampered not only by the characteristics of the new varieties but by lack of awareness of the end users of the technologies. Farmers' awareness about the available improved varieties is therefore critical in the adoption programme. Our results confirm with this preposition. In line with our expectation, access to extension services was statistically significant in explaining the level of adoption. The institutional setting of the farm system has a profound influence on the adoption of technologies and institutional factors like frequent extension contacts are positively related to the adoption decision of farmers (Tesfaye et al., 2001; Habtemariam, 2004). They may merely create social pressure for farmers to use inputs and the methods the agents advocate (Moser and Barrett, 2006). These contacts illustrate that the availability of reliable information sources will enhance the communication process and have significant associations with the adoption of improved technologies. Access to extension services enables farmers to get exposed and more familiar with a new variety. Extension service is one of the most prearranged conditions for creating awareness and building the necessary knowledge for using the innovation following the approach which is most convenient for farmers. Farmers' perception towards IRM for *Striga* was negative and significant in explaining the extent of IRM adoption. The negative sign of the perception variable is unexpected and may be explained by the possibility that farmers' positive perception about IRM has been distorted by other perceptions/attitudes or due to negative correlation between this variable and other varietal characteristics not included in the model. The significance of household size suggests that large households are more likely to invest in new technologies as they can guarantee an adequate supply of farm labour necessary for the expansion of farm enterprises. This may suggest that encouraging them to operate in large number could be regarded as a policy relatively likely to increase productivity. The gap between maize production and consumption per capita was statistically significantly ($P < 0.05$) and supports the hypothesized sign that the deficit of maize production per capita influences positively the adoption of technology. Any household failed to reach the expected level of maize production due to *Striga,* ends in a deficit which is consequently encourage to seek for high-yielding maize varieties to increase its production and therefore likely to adopt IRM. This result confirms the existence of substantial opportunities of increasing maize production via augmenting IRM adoption.

CONCLUSION AND RECOMMENDATIONS

This study provides an analysis of the determinants of adoption of IRM using a DH model due to a hypothesis that factors that affect the decision to adopt IRM may be different from those that influence the extent of adoption. The findings from this study indicate that although in general there is a positive correlation between probability of adoption and intensity of IRM use, we note some differences with regard to the factors that influence the two decisions. Results reveal that age had a positive effect on the decision to adopt while it had no effect on the extent of adoption. The similar effect has been observed with the gap between maize production and consumption per capita, which had a positive effect on the extent of adoption without effect on the decision of adoption. The effect of farmers' perception towards IRM on adoption decision is another example of variable with an opposite effect between the two stages of adoption. Results indicated that while perception leads to increased probability of adoption, it has a negative effect on the extent of adoption. The results indicate also that although membership to any social group increases the likelihood of adoption, it does not influence the extent of IRM area cultivated. These results have a number of implications in terms of sustaining smallholder agriculture already in peril in western Kenya and which are critical for fighting *Striga*. An interesting lesson from this study is that it is important to consider the two stages of adoption in order to improve farmers' ability to adopt, and increase intensity of IRM use because factors that affect the decision to adopt are not necessarily the same factors that affect the decision on the extent of adoption. Factors such as age, household size, extension services, membership to social group, gap between maize production and consumption per capita and perception may enhance or limit adoption and diffusion of IRM technology. To develop a successful *Striga* control programme in the area, these factors have to be taken into consideration focusing first on factors that affect households' decision of adoption. Policy makers and stakeholders of the maize sector are hereby called upon to develop the sector thereby finding strategies regard to the key determinants in order to encourage households in western Kenya to be more decisive in their choice to adopt and intensify IRM technology. This is vital to reduce *Striga* in parallel with poverty.

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