Determinants of Adopting Imazapyr-Resistant Maize Technologies and its Impact on Household Income in Western Kenya

D.B. Mignouna, V.M. Manyong, and J. Rusike
International Institute of Tropical Agriculture (IITA), Tanzania

K.D.S. Mutabazi and E.M. Senkondo
Sokoine University of Agriculture (SUA), Tanzania

This study identifies the adoption determinants and causal impact of adoption of imazapyr-resistant maize (IRM) on income and poverty among maize farming households using a logistic model and Heckman selection-correction model. Results from a randomly selected sample of 600 households consisting of 169 adopters and 431 non-adopters reveal that combined specific household, farm, institutional, and technological factors influence the probability of adoption of the technology. The results also showed that adoption of IRM raises farm household income even after controlling for observable and unobservable household characteristics. Conclusions drawn from this study are that the use of IRM for *Striga* control is a reasonable policy instrument to raise small-farm income and reduce poverty among maize farming households.

Key words: IRM technology, determinants, adoption, impact, Kenya.

Introduction

Adoption of improved agricultural technologies has become a critical avenue of increasing productivity in developing countries, but is subject to serious limitations. In Western Kenya, *Striga* constrains the production of maize, the most important food crop in the country. The situation has emphasized the need of *Striga* control methods. The traditional methods of *Striga* control is comprised of the use of either uprooting and burning or manuring. Although the lower costs requirement of these traditional technologies makes them advantageous and affordable, their inefficiency makes them unfavorable to farmers' needs and goals. Imazapyr-resistant maize (IRM) technology—consisting of coating the seed of herbicide-resistant maize with the herbicide imazapyr—has been found to be favorable and efficient in controlling *Striga* weed (De Groote, Kimenju, Owuor, & Wanyama, 2006; Kanampiu et al., 2006). The technology is comprised of two main elements: imazapyr- and herbicide-resistant maize seed. As the maize germinates, it absorbs some of the herbicide used for coating; the germinating maize stimulates *Striga* to germinate, and as *Striga* attaches to the maize root, it is killed before it can cause damage to the maize plant. Herbicide that is not absorbed by the maize plant diffuses into the soil and kills *Striga* seeds that have not germinated (African Agricultural Technology Foundation [AATF], 2006; International Maize and Wheat Improvement Centre [CIMMYT], 2004). The herbicide used is derived from a naturally occurring gene in maize originally identified by Badische Anlin-& Soda Fabrik (BASF) and made available to CIMMYT (AATF, 2006).

IRM technology has been incorporated in several varieties adapted in Western Kenya to eradicate *Striga*, generate income, and reduce poverty (AATF, 2006).

This study intends to show the impact of IRM technology on poverty after identifying the factors that affect IRM adoption. It also explores the links between the adoption of IRM and poverty status of smallholder farmers. The study is relevant to food policy decisions because if IRM has a pro-poor impact, then policies and programs to support IRM technology could be justified on equity grounds. More specifically, this article addresses three related questions. First, what are the factors affecting IRM adoption? Second, what are the differences in socio-economic characteristics of IRM adopters and non-adopters? Third, how strong is the impact of IRM on household income? In the remaining parts of the article, we discuss the materials and methods, itemize the results and discussion, and provide some recommendations that can contribute to increase the use of IRM technology and strengthen its impact for poverty reduction.

Material and Methods

Study Area

The mean annual rainfall—which ranges from less than 1,000 mm near the shores of Lake Victoria to 2,000 mm away from the lakeshore—is suitable to *Striga*, as it grows well in areas receiving less than 1,500 mm of rainfall per annum (Oswald, 2005). Nyanza and Western provinces around the Lake Victoria zone in Kenya were chosen for this study based on the importance of maize,

which is a major food and cash crop for small-scale farmers, and *Striga*, which constitutes the most important biological constraint to maize production (Manyong et al., 2008).

Data and Methods

The study was conducted using a structured questionnaire containing both closed and open-ended questions of 600 households, comprising 169 adopters and 431 non-adopters of IRM from September to December 2008. A multistage, random sampling procedure was employed to select households from two provinces in Western Kenya, namely Nyanza and Western. First, the provinces and districts were selected based on maize production and level of *Striga* infestation. Second, farmers in each selected district were stratified into two groups—adopters of IRM and non-adopters. Adopters were identified from a list made available by the frontline extension workers, and then the information was confirmed by the farmers. We employed descriptive statistics and the treatment effect model in the data analysis. The t-test was used to test for significance in differences in the socio-economic characteristics of adopters and non-adopters.

The analysis focuses on the household characteristics associated with participation in the adoption process and the impact of IRM on household annual income. Agricultural households in Western Kenya do not specialize in one production area, and the total household income includes income from farm activities, livestock production, off-farm activities, non-farm activities, and remittances. The study examines the impact of IRM on household income rather than on household consumption expenditure because—for many economists—household income would be the indicator of choice to determine economic status (Pozzi & Robinson, 2007); also expenditures in this study area varies considerably among household members.

Theoretical Model

Determinants of Adopting IRM

The study uses a logistic model to estimate the probability that a given household will adopt IRM. Logit regression is a linear probability model for binary response where the response probability is evaluated as a linear function of the explanatory variables (Maddala, 1983; Wooldridge, 2003). The treatment decision is defined as a binary outcome of the use of new varieties by households in the sample, with "1" assigned to households

that were adopters and "0" otherwise. Then, the response probability by household $i(P_i)$ can be expressed as follows.

$$P_i = F(z_i) = F(\beta x_i) = \frac{1}{1 + \exp(-z_i)} = \frac{\exp(z_i)}{1 + \exp(z_i)} , \quad (1)$$

where $F(z_i)$ is the value of the logistic cumulative density function associated with each possible value of the underlying index, and z_i and x_i are the independent variables that will influence this decision; βx_i is a linear combination of the independent variables such that

$$z_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \varepsilon_i , \quad (2)$$

where z_i is the unobserved index level or the logarithm of the odds ratio of the ith observation; β is the parameter to be estimated; and ε_i is a random error or disturbance term.

The coefficients in the logit analysis are estimated using maximum likelihood and serve the purpose of indicating a direction of influence on probability. The marginal effect of each of the independent variables is calculated and indicated by the calculated changes in probabilities (Maddala, 1983).

The adoption of IRM is not a simple process and may be influenced by a number of working hypotheses, similarly to any other new agricultural technologies adoption research (Adesina, Mbila, Nkamleu, & Endamana, 2000; Calatrava-Leyva, Franco, & Gonzalez-Roa, 2005; Herath & Takeya, 2003; Mendola, 2005). It was hypothesized that a farmer's decision to adopt or reject a new technology at any time is influenced by the combined effects of a number of factors. In this study, we hypothesize that the factors influencing IRM adoption include each of the following.

Household-specific Factors. A farmer's age is expected to increase IRM adoption in the sense that older farmers over time have gained farming knowledge and experience and are better able to evaluate technology information than younger farmers. The gender of the household head is hypothesized to relate positively to the adoption of an IRM package. The assumption is that the head of the household is the primary decision maker and men have more access and control over vital production resources than women due to many socio-cultural values and norms. Education level of the household head increases a farmer's ability to obtain, process, and use information relevant to the adoption of IRM. Thus, educated farmers are more likely to adopt IRM. Household

size—a proxy to labor availability—is the major source of labor for farm activities. Large households have the capacity to relax the labor constraints required during IRM introduction. It is expected, therefore, that a larger household size will affect positively the decision of adopting IRM.

Farm-specific Factors. Large land contributes to increased willingness to invest in IRM. As a result, a positive relationship was hypothesized between farm size and IRM adoption. A gap between maize production and consumption per capita is hypothesized to be a stimulant of IRM adoption. The deficit created between maize production and consumption per capita can stimulate the demand for high-yielding varieties.

Institutional Factors. Belonging to a rural social group enhances social capital allowing trust, idea and information exchange. Thus, membership to a group could increase the technology adoption. Access to extension services is hypothesized to increase the adoption after increasing awareness about IRM technology.

Technological Factors. The reason behind the inclusion of perception in this study is that the characteristics of the technology play a critical role in the adoption decision process. Farmers who perceived IRM as being consistent with their needs and compatible to their environment were expected to adopt since they find it as a positive investment. Perception towards IRM for *Striga* control is hypothesized to be positively related to the adoption decision.

Model to Estimate Impact

Adoption and impact of IRM on smallholder farmers were tested with a treatment effects model, also called the Heckman selection-correction model as defined and employed in different ways by Maddala (1983) and Heckman (1995). This model is widely known as the instrumental variable (IV) method, which fits treatment effects models using either Heckman's two-step consistent estimator or full maximum-likelihood. The treatment effects model considers the effect of an endogenously chosen binary treatment on another endogenous continuous variable, conditional on two sets of independent variables. The endogenously chosen binary treatment is the choice to grow the improved variety, controlling for its exposure. Application of the IV method helps to control for the potential endogeneity of use and accrued outcomes. Variables are used as

instruments that influence adoption but not the impacts of adoption. These include membership to social group and contact with extension services as the identifying variables that influence adoption but not income. The choice is dictated by the fact that firstly one cannot adopt IRM variety without being aware of it, and we do observe some farmers adopting IRM (i.e., membership to a social group and contact with extension agents create and increase farmers' knowledge about IRM and consequently does cause adoption). Secondly, it is natural to assume that exposure to IRM towards membership and extension services affects the income and poverty outcome indicators only through adoption (i.e., the mere awareness of the existence of IRM without adopting it does not affect the outcome indicators of a farmer). Hence, the two requirements for membership to social group and contact with extension service variables to be valid instruments for IRM adoption status variable are met. The two-equation system enables the identification of the determinants of technology use (adoption of IRM) as in a logistic regression model, and the characteristics influencing impact (among them the use of technology). Thus, the general form of the instrument variables model is expressed as

$$y_i = x_{1i}\beta_1 + x_{2i}\beta_2 + v_i \dots \tag{3}$$

$$w_i = x_{1i}\gamma_1 + y_i\gamma_2 + \mu_i \dots, \tag{4}$$

where the dependent variables include *y*, which measures adoption and is an endogenous regressor, and *w*, which measures the impacts of adoption. The vector x_1 represents a set of explanatory variables that influence both adoption and impacts, and the vector x_2 includes instrumental variables that explain adoption (dichotomous variable) only. The error terms of the equations, *v* and *μ*, have means of zero but are correlated. *β* and *γ* are parameters.

Results and Discussion

Descriptive Statistics

Evidence from Table 1 reveals that the majority of respondents (74%) were male. There is a higher number of males in non-adopter households than that in adopter households, but the difference was not significant. At the time of the survey, the average age of the household head was 46 years old; the household head's age was significantly different for adopters and non-adopters. The average household had 5.5 members, and adopters had larger households than non-adopters. The farms in

Table 1. Household socio-economic characteristics by adoption status.

Characteristic	Adopters (n=169)	Non-adopters (n=431)	Total (n=600)	Difference test
Age of the HHH (years)	48.92	45.19	46.24	3.73***
Gender of HHH (male=1)	0.71	0.75	0.74	-0.04
Education of HHH (years)	6.81	4.41	5.06	2.40***
HH size (count)	6.22	5.28	5.55	0.94***
Farm size (Ha)	0.85	0.41	0.53	0.44
Maize land (Ha)	0.41	0.47	0.46	-0.06**
Oxen use (use=1)	0.20	0.04	0.08	0.16***
Active family labor force (count)	3.03	2.73	2.81	0.30***
Gap between maize production & consumption per capita (Kg)	-116.66	8.21	-26.96	-124.87
Membership (yes=1)	0.75	0.58	0.63	0.17***
Access to extension service (yes=1)	0.70	0.39	0.48	0.32***
Perception towards IRM for *Striga* control (positive=1)	0.96	0.72	0.79	0.25***
Province	0.40	0.54	0.50	-0.14***
Total household income (Kshs)	80,971.96	43,032.74	53,718	3.79***
Household income per capita (Kshs)	15,466.8	9,319.12	11,050	6.15***
Household income per capita (US $)	214.82	129.43	153.48	85.38***

Note: The T-test was used to test for difference in socio-economic/demographic characteristics between adopters and non-adopters. Statistical significance at 10% (*), 5% (**) and 1% (***); HHH= household head; US $1 = 72 Ksh

both groups are small, with less than one hectare of cultivated land. Active labor availability is higher in adopter households when compared with those of non-adopters, and the difference is significant at 1%. There is a significant difference in the years of schooling of the household heads among adopters and non-adopters, with the former being more educated. There was no significant difference observed between adopters and non-adopters in terms of gap between maize production and consumption per capita. Adopters had significantly higher contact with extension visits than non-adopters. Farmers were engaged in different income generating activities, and the main sources of income include crop and livestock selling; the results show that there is a significant (at 1%) difference between the gross incomes of adopters and non-adopters, and there is also a significant (at 1%) difference in the ability to purchase per head by both groups. As is evident from the table, IRM adopters are better off than non-adopters. However, the differences in observed mean outcomes between adopters and non-adopters cannot be entirely the effect of IRM adoption due to the problem of self-selection and non-compliance (Heckman & Vytlacil, 2005; Imbens & Angrist, 1994).

Determinants of IRM Adoption

Six out of nine explanatory variables tested were significant in explaining the adoption of IRM (Table 2). The significant variables were age of household head, education of household head, household size, membership to social group, access to extension services, and perception of IRM. Age of household head, education of household head, and household size were the household specific characteristic that scored significant differences on IRM adoption. The positive association on age and adoption indicates that the older the household head, the greater the chances of adopting the improved technology. Similar relation was found with the education level and household size. Institutional factors, such as membership to social group and access to extension, as well as source of farmers' exposure had significant influence on IRM adoption. Adoption increased with farmers' perception towards IRM for *Striga* control. Farmers who perceive IRM as beneficial to them would adopt it more than those who have a negative or indifferent perception. However, farm-specific factors were not significant variables in determining adoption of IRM technology. Gender was the only household-specific factors with any impact on IRM adoption. This implies that the chance of adoption was less for female-headed households or household heads who were married with their main occupation being farming. Contrary to that,

Table 2. Determinants of IRM adoption.

Variable	Coefficient	Std. error	P>|z|	dy/dx
Age	0.1461	0.0174	0.0000***	0.0205
Gender	-0.5064	0.2786	0.0690	-0.0770
Education	0.5760	0.0603	0.0000***	0.0809
Household size	0.1443	0.0610	0.0180**	0.0203
Farm size per household	-0.0098	0.0187	0.6000	-0.0014
Gap between maize production & consumption per capita	-0.0002	0.0002	0.3290	-0.0001
Membership to social group	0.6077	0.2574	0.0180**	0.0813
Access to extension services	0.7560	0.2505	0.0030***	0.1076
Perception towards IRM for *Striga* control	2.3141	0.4884	0.0000***	0.2168
Constant	-14.2914	1.3318	0.0000***	
Number of observations		573		
LR chi^2 (9)		265.35		
Prob > chi^2		0.0000		
Pseudo R^2		0.3818		

*** significant at 1%, ** significant at 5%, * significant at 10%

Table 3. Estimated impact of improved varieties on household annual income.

Variable	Treatment equation (participation in adopt)		Impact equation (average expected household income)		Marginal effect
	Coef.	Std. err.	Coef.	Std. err.	dy/dx
Age	0.0837***	0.0095	632.603**	291.4338	0.02197
Gender#	-0.251	0.1578	8,455.039*	4,415.363	-0.06932
Education	0.324***	0.0317	1,468.175	1166.4	0.08511
Household size	0.073**	0.0344			0.01920
Farm size per household	-0.005	0.0102	48.194	175.9354	-0.00130
Gap between maize production & consumption per capita	-0.0001	0.0001			-0.00002
Membership to social group#	0.331**	0.1464			0.08337
Access to extension services#	0.441***	0.1424			0.11651
Perception towards IRM for Striga control#	1.281***	0.2564			0.23195
Active family labor force			6,648.316***	1,863.82	
Oxen use			13,385.96*	7,032.467	
Adoption			26,093.76**	11,277.7	
Cons	-8.094	0.7004	-14,916.25	17,556.830	
lambda			1,886.252	7,106.772	
rho		0.04124			
sigma		45,740.006			
Number of observations		573			
Wald chi^2 (11)		182.17			
Prob > chi^2		0.0000			

*** significant at 1%, ** significant at 5%, * significant at 10%, # dy/dx is for discrete change of dummy variable from 0 to 1.

chance of adoption increased with number of years spent in school and number household members who were involved in fulltime farming.

IRM Impact

The results of the treatment effects regression are presented in Table 3. Likewise, the selection equation,

which predicts participation in IRM adoption, gives similar results to those of the logit model presented in Table 2. The results of the outcome equation, which predicts household income and is displayed in Table 3, showed that the average expected income obtained by adopters is significantly (at 5%) more than that obtained by non-adopters—Ksh 26,093.76 (US $362). Farmers have then realized their impact on household income even though it is still low. The estimated rho coefficient is statistically significant, implying the existence of selection bias, so it was necessary to estimate household income using the treatment effects regression model. The effect of adopting IRM on household income is positive and statistically significant.

Conclusion

The article examined the factors influencing IRM adoption and revealed that age, education, household size, membership to social group, access to extension services, and farmer's perception of IRM are responsible for increasing the probability of IRM adoption. Significant differences in age, education, household size, use of oxen, active family labor force, membership, access to extension service, perception of IRM, and income were found between the adopters and non-adopters. The treatment effects model has proven the presence of bias in the distribution of covariates between adopters and non-adopters. Adoption of IRM helped raise farmers' income, thereby increasing their probability of reducing poverty. However, IRM adoption still low. This suggests that intervention programs to help scale-up IRM in *Striga*-infested areas is therefore a reasonable policy instrument to raise incomes in these areas, although promotion and dissemination of the technology are needed also to improve the adoption rate and strengthen the impact.

References

African Agricultural Technology Foundation (AATF). (2006). *Empowering African farmers to eradicate Striga from maize croplands*. Nairobi, Kenya: Author.

Adesina, A.A., Mbila, D., Nkamleu, G.B., & Endamana, D. (2000). Econometric analysis of the determinants of adoption of alley farming by farmers in the forest zone of southwest Cameroon. *Agriculture, Ecosystems, and Environment*, *80*, 255-265.

Calatrava-Leyva, J., Franco, J.A., & Gonzalez-Roa, M.C. (2005, August). Adoption of soil conservation practices in olive groves: The case of Spanish mountainous areas. Paper presented at the XI International Congress of the European Association of Agricultural Economists, Denmark.

International Maize and Wheat Improvement Center (CIMMYT). (2004). Striga *weed control with herbicide-coated maize seed*. Texcoco, Mexico: Author.

De-Groote, H., Kimenju, S., Owuor, G., & Wanyama, J. (2006). Market liberalization and agricultural intensification in Kenya (1992-2002). Paper presented at the 26th Conference of the International Association of Agricultural Economics, Gold Coast, Australia.

Heckman, J. (1995). Randomization as an instrument variable. *Review of Economics and Statistics*, *77*(2), 336-341.

Heckman, J., & Vytlacil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation. *Econometrica*, *73*, 669-738.

Herath, P.H.M.U., & Takeya, H. (2003). Factors determining intercropping by rubber smallholders in Sri Lanka: A logit analysis. *Agricultural Economics*, *29*, 159-168.

Imbens, G.W., & Angrist, J.D. (1994). Identification and estimation of local average treatment effects. *Econometrica*, *62*(2), 467-475.

Kanampiu, F., Omanya, G., Muchiri, N., Nang'ayo, F., Werehire, P., Tyrell, D., & Sthamer, V. (2006, July 5). Launch of STRIGAWAY (IRM) technology for *Striga* control in Africa. *Proceedings of the Launch of the STRIGAWAY (IRM) Technology*, 5-62.

Maddala, G.S. (1983). Limited dependent and qualitative variables in econometrics. Department of Economics, University of Florida. Cambridge University Press, United Kingdom, 401pp.

Manyong, V.M., Alene, A.D., Olanrewaju, A., Ayedun, B., Rweyendela, V., Wesonga, A.S., et al. (2008). *Baseline study of Striga control using imazapyr-resistant (IR) maize in Western Kenya*. Nairobi, Kenya: African Agricultural Technology Foundation and the International Institute of Tropical Agriculture.

Mendola, M. (2005). *Agricultural technology and poverty reduction: A micro-level analysis of causal effects* (Working Paper No. 2005-14). Milan, Italy: Universita degli Studi di Milano Bicocca.

Oswald, A. (2005). *Striga* control-technologies and their dissemination. *Crop Protection*, *24*, 333-342.

Pozzi, F., & Robinson, T. (2007). *Intergovernmental Authority on Development (IGAD) Livestock Policy Initiative: Poverty and welfare measures in the Horn of Africa* (IGAD LPI Working Paper No. 08-08). Addis Ababa, Ethiopia: FAO Ethiopia.

Wooldridge, J.M. (2003). *Introductory econometrics. A modern approach*. Mason, OH: Thomson South-Western.

Acknowledgements