The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

AfJARE African Journal of Agricultural and Resource Economics
African Journal of Agricultural and Resource Economics Volume 16 Number 3 pages 216-236
doi.org/10.53936/afjare.2021.16(3).15

Is change worth it? The effects of adopting modern agricultural inputs on household welfare in Rwanda

Aimable Nsabimana
Department of Economics, University of Rwanda, Kigali. E-mail: aimeineza@gmail.com

Abstract

This study investigates the driving factors that influence farmers' decisions to adopt modern agricultural inputs (MAI) and how this affects farm household welfare in rural Rwanda. To account for heterogeneity in the MAI adoption decision and unobservable farm and household attributes, we estimate an endogenous switching regression (ESR) model. The findings reveal that size of land endowment, access to farm credit and awareness of farm advisory services are the main driving forces behind MAI adoption. The analysis further shows that MAI adoption increases household farm income, farm yield and equivalised consumption per capita. This implies that adopting MAI is the most consistent and potentially best pathway to reduce poverty among rural farmers. The study hence suggests that policymakers should align the effective dissemination of MAI information and farm advisory services, strengthen farm credit systems and improve market access – most crucially at affordable prices – among small-farmers throughout Rwanda.

Key words: modern agricultural inputs; welfare effect; endogenous switching regression; Rwanda

1. Introduction

Sub-Saharan Africa (SSA) continues to face endless food shortages. The region is characterised by a high incidence of malnutrition and food insecurity. Although the continent contains around 60% of the world's uncultivated arable land, SSA remains a net importer of food. A number of driving factors that induce food shortages include unpredictable weather, which often results in production uncertainty and unforeseen hardships for farm households, and the limited uptake of modern farm inputs, which leads to lower farm yields and complete harvest failure, resulting in constant, severe food shortages and welfare losses. Hence, these factors cause the farm yield across most of the SSA countries to be inadequate for achieving food security (Sánchez 2010). To improve farm productivity for smallholder farmers in particular, households need to adopt modern agricultural inputs (MAI). These include the use of improved seeds, fertiliser and pesticides, and better ways of planting and weeding.

However, despite its potential benefits, the adoption of MAI has been inconsistent and slow in some farming systems, especially in SSA countries. This delay, and the erratic use of new and more appropriate seed varieties, fertilisers and pesticides in many parts of SSA, have led to production failures and ultimately have left the region with persistent hunger, food insecurity for families and a high prevalence of poverty (Barrett 2013). Furthermore, the extant literature has also associated the delay and low input uptakes with farm credit constraints, barriers to adequate information, poor institutional arrangements and environmental factors, all of which lead to excessive production costs (Barrett *et al*. 2004; Abdulai & Huffman 2014).

In addition, many driving forces have been attributed to the low farm yield in the agricultural sector in the region. These include negative effects resulting from climate change (Jayne *et al*. 2018), the limited adoption rate of modern farm inputs (Abdulai 2016), and poor and unsustainable farming practices (Graboswki *et al*. 2016), among others. It further has been also noticed that adopting modern farm inputs allows farmers to deal with very serious issues related to climate change (Chavas & Shi 2015) and the rain-fed nature of farm production (Dzanku *et al*. 2015; Tesfaye *et al*. 2019). From these binding constraints, the use of modern farm inputs in the agricultural sector in SSA is a sine qua non condition for improving the agricultural sector and wellbeing of a significant number of households that depend crucially on the farm sector. It is also important to mention that the use of MAI could improve the fertility of the soil and the yield of crops (Khonje *et al*. 2018; Tesfaye *et al*. 2019).

The main objective of this study therefore was to examine the effects of MAI adoption on the welfare of farmers. The MAI evaluated in this study are improved seed varieties, inorganic fertilisers, pesticides and water conservation practices. The study was carried out against the backdrop of low farm yield in Rwanda due to reliance on rain-fed agriculture, high levels of poverty and declining soil fertility associated with nutrient depletion and soil erosion (Morris *et al*. 2007).

The purpose of this research, firstly, was to complement the extant literature on understanding farmers' decisions to adopt MAI in Africa, focusing on Rwanda. The fact is that Rwanda is a subsistence farming country, where more than 75% of households depend daily on farming (World Bank 2011). The research findings on farm technology therefore would be useful for policy makers in helping them to design adequate and sustainable agriculture that can provide an optimal food supply to meet the needs of the market. Second, we focus on the farm yield, income and farmers' consumption expenditure (including net household welfare), as motivated by their implications for achieving food security. Moreover, the use of farm yield and farm income seems particularly appropriate in the Rwandan context. The country has initiated various farm policies, including land use policy and a land consolidation programme (CIP). The latter was introduced in 2008 with the overall goal of ensuring sustainable land management and improving farm yields (Ministry of Agriculture 2011a). Under this programme, the country aimed to enhance the farm productivity of priority crops, namely beans, maize, Irish potatoes, cassava, wheat and soybean, and the provision of farm inputs, such as improved seeds and chemical fertilisers. As is the case in many other African countries, Rwanda has faced intensive demographic pressure over the last decades, and this has also created massive pressure on land use (both extensive housing and farming on fragmented land). Hence, examining the effect of MAI on the welfare of smallholder farmers in Rwanda is crucial to understand technology adoption processes and will offer scientific lessons for many other African countries facing the challenges of high population pressure, high fertility rates, urbanisation, unbalanced diets, food insecurity, malnutrition and low uptake of inputs.

To conduct the study, we applied an endogenous switching regression (ESR) model based on farm household-level data collected from the national living standard household survey of Rwanda. The former is very robust and an effective econometric technique that accounts for selectivity bias to identify the welfare implications of MAI for smallholder farmers. By using the ESR technique, I was able to derive unbiased treatment effects of MAI adoption on farm household welfare, and also considered that MAI adoption may systematically change the production elasticities of farm inputs and other relevant factors (Kabunga *et al*. 2011).

The findings from this study provide evidence of direct and indirect effects of MAI adoption on farm household wellbeing. This will be of significant relevance for better understanding the yield effects of MAI in Rwanda and other countries. An assessment of the empirical evidence is also important for policy-making purposes (Winters *et al*. 2011), for example when designing and implementing effective support measures.

The rest of the paper is organised as follows: Section 2 illustrates what is known about MAI adoption in Rwanda. Section 3 explains the data sources and descriptive statistics, while section 4 presents the theoretical model and the employed estimation techniques. Section 5 presents and discusses the study's findings. The last section concludes and provides policy implications.

2. What is known about MAI adoption in Rwanda?

Agricultural policies in Rwanda are implemented under crop intensification programmes (CIP), with the aim of sustainably improving agricultural productivity through procuring improved seeds, fertilisers and pesticides for farmers to increase crop production potential (Cantore 2011). In line with boosting MAI adoption among small-scale farmers, different national policies have been proposed, e.g. establishing the National Seed Service in 2001, the Seeds Law in 2003, the Seeds Commodity Chain Project in 2005 and the National Seed Policy in 2007 (Kelly *et al*. 2001; African Seed Traders Association [AFSTA] 2010). Moreover, CIP promotes new farming techniques among farmers with the aim of assisting them to access new, improved agricultural inputs and to increase agricultural productivity in food crops with high yield potential (beans, potatoes and maize, among others), thus ensuring food security and self-sufficiency (Ministry of Agriculture 2011b). Under the CIP, farmers, especially those involved in cooperatives and land consolidation programmes, are supported to access farm inputs in the form of cooperative vouchers and, to a limited extent, farm credits under the so-called Business Development Fund (BDF) projects.[1] Besides, agriculture is still the main sector of economic growth in Rwanda; it employs approximately 80% of the total labour force and generates more than 43% of the country's export revenues. Despite significant interventions by government and stakeholders, the number of farmers using MAI is still insignificant. For instance, the National Institute of Statistics of Rwanda ([NISR] 2015) showed that only 11.6% of smallholder farmers used improved seeds, while the use of inorganic and organic fertilisers was only 14.6% and 43.1% respectively during cropping season B in 2015.[2] The adoption of MAI is also unimpressive in large-scale farming, where improved seeds were used by 40% of farmers, while organic and inorganic fertilisers were used by 42.3% and 51.5% of the farmers respectively during season B. In this study, a farmer was considered to have adopted MAI if he/she had used at least two or more of the selected inputs over the 12 months prior to the survey, otherwise the farmer was regarded as a non-adopter.

3. Data source and descriptive analysis

The data used in this study was extracted from the Third Integrated Household Living Conditions Survey of Rwanda (EICV3), conducted in 2010/2011 by the NISR, together with the World Bank and the EU, which provided financial and technical support. The survey encompassed the entire country and included all four provinces, with the South, East and West provinces each accounting for 31%, 28% and 21% of the sampled farm households respectively, while the Northern province accounted for 19% of the sample.[3] The sample was restricted to households with farm activities to ensure that all households in the adopt and non-adopt groups had engaged in farm economic activities in the 12 months before the survey was conducted (see Table 1). EICV3 provides information on household farm income and farm yield level.

[1] Initiated in 2009, BDF is a government project aimed at enhancing financing for small and medium-sized businesses, especially those with innovative projects and employment potential. Since its implementation, BDF has made significant contributions, especially to small-scale businesses – including farmers, who get access to farm credits.

[2] Rwanda has three main agricultural seasons (A, B and C). Season A runs from September to January and season B from February to May; both A and B are rainy seasons. The quantity of rainfall that occurs has a direct effect on crop production and hence on food market prices. Season C runs from June to September and is a dry season, during which large crop harvests take place, especially of grain crops such as rice, maize and wheat, and starch crops such as cassava and tuber potatoes, among others.

[3] To minimise the bias, city dwellers were removed from the study, as we were interested in farming, which is undertaken mainly by rural inhabitants.

Table 1: Descriptive statistics of household and farm characteristics of adopters and non-adopters

Variables	Description	Adopters	Non-adopters	Difference	T-values
	Outcome variables				
Income	Total farm income (Frws)	55 165.05	27 638.72	27 526.34	16.22
Consumption	Expenditure per capita (Frws)	16 611.91	12 628.77	3 983.14	12.62
Farm yield	Farm yield (kg/ha)	1 384.18	871.99	512.19	17.81
	Farm and household characteristics				
Age	Average age of household head (HH)	41.22	43.67	-2.45	-5.53
Farm size	Land area owned by HH (hectare)	0.85	0.56	0.29	6.53
Household size	Household size	5.35	4.66	0.69	10.62
Gender	Gender of HH head (1 = male & 0 = female)	0.86	0.73	0.13	10.44
Consolidation	HH involved in land consolidation (yes = 1)	0.40	0.14	0.26	19.02
Credit	HH access to farm credit (yes = 1)	0.16	0.05	0.11	11.32
Nonfarm	HH ran non-farm business (yes = 1)	0.49	0.35	0.14	8.99
Irrigation	HH involves in irrigation practice (yes = 1)	0.19	0.08	0.11	10.19
Clean water	HH lives close to clean water (yes = 1)	0.86	0.85	0.01	0.85
Education	HH head with formal education (yes = 1)	0.70	0.57	0.13	8.59
Awareness	Awareness of agricultural policy (yes = 1)	0.36	0.14	0.22	16.35
	Farm household location				
South	Southern Province (yes = 1)	0.27	0.37	-0.10	-6.55
West	Western Province (yes = 1)	0.27	0.15	0.12	9.39
East	Eastern Province (yes = 1)	0.20	0.37	-0.14	-10.57
North	Northern Province (yes = 1)	0.26	0.11	0.16	12.53
	Number of farm households sampled	2 243	1 847		

Note: Frws: Rwandan Francs. Note that the average exchange rate in 2011 was: $1 = 604 Frws

The total sample size used in this study is 4 090, where the percentage of adopters and non-adopters is 55% and 45% respectively.[4] The study used three outcome indicators to measure the effect of MAI adoption on farmers' welfare, as shown in Table 1. These are farm income, farm yield and consumption per capita. Farm income was taken as total agricultural revenue and farm yield as farm production per hectare (expressed in kilograms) that each household reported as total harvested outputs. Household consumption per capita was computed using total household expenditure and household size, reflecting the degree of expenditure among smallholder farmers. Using farm yield and farm income variables provided relevant indicators of farmers' production performance among smallholder farmers in Rwanda. On the other hand, to assess the level of utility between MAI adopters and non-adopters, we used household consumption/expenditure per capita (Syrovátka 2007).

Table 1 exhibits the definitions and mean differences of adopters and non-adopters of key explanatory variables used in this study. It provides a basic statistical comparison between farm households that used MAI and those that did not. The treatment variable, 'adopters or non-adopters', is a dummy with the value of 1 if the farm household had used at least one of the three or more of the MAI (improved seeds, inorganic fertiliser or pesticides) in the past 12 months before the survey was conducted. To control for differences in farm household decisions, the household size, age, gender and the education level of the household heads was considered. The study similarly also controlled for the farm characteristics, which include land size (expressed in hectares) and other important set of dichotomous variables, such as whether the farmers benefited from farm credits, were involved in off-farm business or in the land consolidation programme, among others. The data reveals that, on average, household size of adopters was larger than that of non-adopters. The majority of the farm household heads had formal education (70% and 57% for adopters and non-adopters respectively).

[4] The final sample was decided after removing all farm household with incomplete information and doing data cleaning.

4. Methodology and estimation techniques

4.1 Adoption decision and selection bias

As in other SSA countries, rural livelihoods in Rwanda are characterised by limited employment opportunities besides for farming activities. The limited access to input markets and merit goods, and poor infrastructure, among others, lead to high level of market failure. These market imperfections translate into poverty, high transaction costs and underdevelopment for both the off-farm and farm sectors. In this situation, it is difficult for rural households to access credit to purchase farm inputs to increase agricultural productivity. Therefore, because of such conditions, the consumption and production of rural households are not independent of one another. This means that farm household resources are simultaneously allocated to off-farm labour supply and to on-farm activities like MAI adoption (De Janvry *et al*. 1991; Asfaw *et al*. 2012). In such a scenario, it is possible that the adoption of MAI by farmers would have positive effects on their welfare through increased crop yield, farm income and employment opportunities, both inside and outside farming. In this respect, MAI adoption could be expected to generate a high level of consumption, food market stability, higher farm income and reduced poverty levels among households. The adoption of MAI would also free up household resources for alternative uses and broadly improve farm household welfare. To model this type of farm household behaviour, we assumed that farmers' choice decision to adopt can be represented by the random utility framework (Kabunga *et al*. 2012). For risk-neutral farmers, the decision to adopt is based on comparing the expected utility of wealth from adoption, $U^A(\omega)$, against wealth of not adopting, $U^N(\omega)$, with (ω) representing the amount of wealth. Therefore, farmers will adopt only if $U^A(\omega) > U^N(\omega)$. The difference between utilities from adoption and non-adoption can be expressed as:

$$L^*_h = U^A(\omega) - U^N(\omega), \tag{1}$$

with L^*_h being a latent variable to denote the difference between utility from MAI adoption, $U^A(\omega)$, and the utility from non-adoption, $U^N(\omega)$. However, utilities are unobservable and can be expressed as a function of observable elements in the following model:

$$L^*_h = \mathbf{X}_h\boldsymbol{\eta} + \mu_h, \text{ with } L_h = \begin{cases} 1 & \text{if } L^*_h > 0 \\ 0 & \text{otherwise,} \end{cases}, \tag{1}$$

such that farm household h will choose to adopt ($L_h = 1$) by applying some of MAI in his/her farm production strategies with the aim of improving farm yield, if $L^*_h > 0$, and 0 otherwise. The vector $\mathbf{X}_h$ represents farm and household characteristics that affect the expected benefits of MAI adoption. The characteristics are considered as driving factors of farmers' adoption decision; $\boldsymbol{\eta}$ is a coefficient vector to be estimated, and μ_h is the error term. To measure the effect of adoption, a baseline model is presented, as follows:

$$\mathbf{Y}_h = \mathbf{Z}_h\gamma + \delta L_h + \varepsilon_h, \tag{3}$$

where $\boldsymbol{Y_h}$ is vector of outcome variables (farm income, productivity and expenditure per capita, all three expressed in logarithms); L_h is an indicator variable for MAI adoption, as defined earlier; $\boldsymbol{Z_h}$ is a vector of farm and household characteristics (such as education, age, land size); γ and δ are the vectors of parameters to be estimated; and, finally, ε_h is the stochastic disturbance term. From equation (3), the effect of MAI adoption is measured by parameter δ. However, for δ to be consistent in measuring the effect of MAI adoption on farmers, it must be assigned randomly within the adopter and non-adopter groups (Faltermeier & Abdulai 2009; Kassie *et al*. 2011). Unfortunately, the adoption decision is not random in the case of the current dataset, thus inducing self-selection bias. The farmers' adoption decision depends on a set of observable and unobservable farm and household characteristics that may be correlated with outcome values. These characteristics include farmers' management skills, farm size, land fertility, farm landscape, government policies, farmers' awareness of MAI adoption, farm neighbourhood and many others. This leads to violation of the orthogonality assumption, i.e. $E(L_h, \varepsilon_h) \neq 0$. Different approaches have been suggested to deal with self-selection bias. Heckman (1979) proposed a two-stage method dealing with a self-selection problem when the correlation between two error terms is greater than zero. However, the approach accounts for selection bias in unobservables only by treating the selectivity as an omitted variable problem (Abdulai & Huffman 2014). The second approach is the propensity score matching (PSM) method proposed by Rosenbaum and Rubin (1983), which has been used extensively with impact evaluation analysis in various studies (Jalan & Ravallion 2003; Faltermeier & Abdulai 2009; Kassie *et al*. 2011). However, concerns have been expressed in the literature that PSM can only account for observable factors (Ma & Abdulai 2016). This is a major drawback with the approach, as most of the treatments have unobservable factors that also need to be considered to identify individual treatment effects on outcomes.

In the current study, we examined the driving forces of MAI adoption and the effects of adoption based on the endogenous switching regression (ESR) model. Using the ESR model, we simultaneously estimated the factors and effect of MAI adoption by also accounting for both observable and unobservable factors. The model further allowed us to account for selectivity bias in deriving the effect of adoption on the outcomes. Developed by Lee (1982), the ESR method is a generalisation of Heckman's selection correction approach. The method accounts for unobservable heterogeneity by considering the selectivity as omitted variable bias (Heckman 1979). Unlike the Heckman model, our outcome variables in this study includes farm income and yields that can be observed for the whole sample for both MAI adopters and nonadopters. Therefore, using the ESR model, the farm households were subdivided following their classification as adopters and nonadopters, and this allowed us to identify the statistical differences between the two groups.

4.2 Endogenous switching regression model

By using the ESR model, we were able to account for potential selection bias where the unobserved factors – ε_h in equation (3) and μ_h in equation (2) – are correlated. Therefore, this means that the correlation coefficient of error terms $\rho = corr(\varepsilon_h, \mu_h) \neq 0$. We used the ESR model to estimate the potential outcomes on farm income, yield and expenditure per capita in households. The expected outcome equations in the two regimes, (1) for adopters and (2) for non-adopters, are expressed as follows:

Regime 1: $Y_{1h} = \alpha Z_{1h} + \varepsilon_{1h}$ if $L_h = 1$ (4a)

Regime 2: $Y_{2h} = \alpha Z_{2h} + \varepsilon_{2h}$ if $L_h = 0$, (4b)

where Y_{ih} represents the outcome variables in regimes 1 and 2, Z_{ih} are the vectors of farm and household demographics that are assumed to influence the outcome variables, ε_{ih} are the error terms, and α represents a vector of parameters to be estimated. The ESR model allows the overlapping of the X_{ih} from equation (2) and the Z_{ih} from equations (4a) and (4b). For identification purposes, exclusion restriction should hold, which implies that at least one variable in X should not appear in vector Z (Maddala 1983; Di Falco *et al*. 2011). In this study, the variable farmers' awareness of public agricultural policies and non-farm business residuals are the selected instruments. The assumption is that these instruments are related to farmers' information sources. We examined the validity of this instrument by performing a falsification test. If a variable is a valid instrument, it should affect the MAI adoption decision but not the outcome variables (farm income, farm yield, household and consumption per capita level) among farmers who did not adopt. The test results indicate that the selected instruments were statistically valid. The results presented in Table A.2 in the appendix indicates that nonfarm business residuals and public awareness of agricultural policies can be considered as valid selection instruments. They are statistically significant factors that affect farmers' decisions to adopt or not to adopt MAI, with adopt, $\chi^2 = 3.01$, p = 0.082; and $\chi^2 = 12.6$, p = 0.000 for nonfarm business and awareness variables respectively. But the same variables are not different from zero for farm income, farm yield and farm household expenditure per capita, with F-test = 0.28, p = 0.593; and F-test = 2.42, p = 0.120 respectively. More details on the validity of falsification test results are provided in Table A.2 of the appendix.

To estimate the endogenous switching model efficiently, we used the full information maximum likelihood (FIML) estimation approach of Lokshin and Sajaia (2004), of which the logarithmic (log F) likelihood function is defined as:

$$Log\ F = \sum_{h=1}^{N} L_h \left[\ln \phi(\frac{\varepsilon_{1h}}{\sigma_1}) - \ln \sigma_1 + \ln \Phi(\theta_{1h}) \right] + (1 - L_h) \left[\ln \phi(\frac{\varepsilon_{2h}}{\sigma_2}) - \ln \sigma_2 + \ln(1 - \Phi(\theta_{2h})) \right], \quad (5)$$

where $\theta_{ih} = \frac{(X_h \eta + \rho_i \varepsilon_{ih} / \sigma_i}{\sqrt{1 - \rho_i^2}}$, $i = 1, 2$ and ρ_i is the correlation coefficient between the error term, μ_h, in selection equation (2) and the error terms, ε_{ih}, in equations (4a) and (4b) respectively.[5]

It is important to highlight that, with the ESR estimations, the sign of the correlation coefficient (ρ) is important. If the value is significantly different from zero, this is an indication of selection bias. If $\rho > 0$, this is an indication of negative selection bias, meaning that farmers with values below the mean value of farm income, farm yield and per capita consumption are more likely to adopt MAI. If $\rho < 0$, this indicates a positive selection bias, implying that farmers with above-average farm income, farm yield and consumption per capita are likely to adopt MAI. The issue of endogeneity in the adoption decision of the farm households, and computing the welfare implications of the MAI uptake, are well documented in the Appendix 1 and Appendix 2 respectively. To derive the welfare impact of MAI updates on the farm households, we compared the expected outcomes of the farm households that actually adopted MAI and those that did not, as indicated in Table A.1 in the Appendix.

5. Results and discussion

The first, fourth and seventh columns in Table 2 present estimates of the selection equation (2) on adopting or not adopting MAI, while the remaining columns provide outcome equations (4a) and (4b) for farmers who did and did not adopt MAI.[6] As explained in section 4.2, the identification of parameters requires that at least one variable must appear in the selection equation and not in the outcome equations. In estimating the ESR model, we incorporated variable awareness, standing for farmers' awareness of agricultural policies as an identified instrument. In this respect, we assumed that farmers' awareness of MAI would induce a significant effect on their MAI adoption decision, but not directly on farm income, farm yield and household consumption level. In addition, in all cases, the coefficient of the variable that represents the residuals from the first-stage regression of the

[5] To estimate the ESR model, Stata commands developed by Lokshin and Sajaia (2004) provided useful tools in this study.
[6] The full information maximum likelihood approach was estimated using Stata version 14.

potential endogenous variable, "non-farm" business, was also included in each selection equation. The coefficient estimates of the residuals from the non-farm business variable were not statistically different from zero, which is an indication that the coefficient had been estimated consistently (Wooldridge 2002).

5.1 The determinants of MAI adoption

Table 2 contains the main driving factors that affect farmers' decisions to adopt or not to adopt MAI. The results in the first, fourth and seventh columns have similar variable names. They are furthermore interpreted as normal probit coefficients and, in addition, they represent the probability of adopting MAI and have similar effects of adoption. The econometric results indicate that farm households with a male head were more likely to adopt MAI. Furthermore, the effect of the age variable was negative and statistically significant in all the selection equations. This suggests that the older farmers are, the less likely they are to adopt MAI on their farms. This finding is consistent with the existing literature (Abdulai 2016; Abdulai & Huffman 2014; Di Falco *et al*. 2011). The econometric results also show that household size is very important in increasing the likelihood that farmers will adopt MAI.

Similarly, the level of education of the household head was found to play a significant role in determining farmers' decisions to adopt MAI. In particular, it was found that a farm household head with any formal education increased his or her probability of adopting MAI much more than those who had no education. Furthermore, the estimated coefficient associated with farm credit was significantly different from zero, which is an indication that farm households with farm access to credit are more likely to adopt MAI. Similar results have been reported by Abdulai and Huffman (2014), who found that less liquidity-constrained farmers are more likely to adopt MAI, hence confirming the role played by farm credit in the MAI adoption decision. The non-farm variable, a proxy for household resource endowment, was positive and statistically significant in all specifications, indicating that farmers with non-farm businesses are more likely to adopt modern agricultural inputs. This implies that income from off-farm businesses is likely to empower households economically to invest in their farming activities via the adoption of MAI, particularly given that the cost associated with MAI adoption is non-trivial. Asfaw *et al*. (2012) also showed that off-farm income is an influential factor in decisions to adopt farm technology. Land consolidation and irrigation practices are used to account for institutional perspectives on MAI adoption. In addition, the household farm size is another driving factor that increases the likelihood that farmers will adopt MAI. The results also show that, when farmers are involved in land consolidation and/or land irrigation practices, the probability of using MAI increases significantly. Finally, regional dummies were used to control for the effects of farm location and MAI adoption decision. The results reveal that the probability of using MAI by farm households is higher in the Western, Northern and Southern provinces than in the Eastern province.

5.2 Effects of determinants and outcome values

The effects of determinants on farm income, farm yield and household consumption are presented in Table 2 for adopters and non-adopters. For the model specifications, the coefficient estimates obtained for a given explanatory variable for adopters and non-adopters differ from each other either in terms of size or signs, thus indicating the presence of heterogeneity in the two groups. Similar results have been found in previous studies (Abdulai & Huffman 2014; Asfaw *et al*. 2012). The effect estimates of education on farm yield and farm household consumption are statistically significant for both adopters and non-adopters and show a positive effect, thus implying that the more the household head is educated, the more likely their farm yield and consumption will increase. Interestingly, the positive and statistically significant coefficient values associated with the farm size variable are an indication that farmers with larger farms tend to experience a rise in their farm income, yield and consumption level. In Rwanda, nearly 83% of the population live in rural areas, and the majority cultivate crops on less than one hectare (Nilsson 2018; Nsabimana *et al*. 2021). Hence, in a country where the average landholding is roughly 0.3 ha per household, the uptake of modern farm inputs such as hybrid seeds, fertilisers and pesticides would positively improve sustainable farm yield and hence food security.

Table 2: Estimating the ESR model for adoption and effects of MAI adoption on household consumption per capita, farm income and farm yield

Variables	Household expenditure per capita			Household farm income			Household farm yield		
	Selection (1)	Adopter (2)	Non-adopter (3)	Selection (4)	Adopter (5)	Non-adopter (6)	Selection (7)	Adopter (8)	Non-adopter (9)
Constant	-1.926***	9.063***	9.080***	-1.757***	10.804***	7.976***	-1.808***	6.916***	5.532***
	(0.194)	(0.158)	(0.111)	(0.212)	(1.264)	(0.149)	(0.177)	(0.442)	(0.096)
Age	-0.011***	-0.001	0.000	-0.010***	0.004	-0.002	-0.010***	0.003	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)	(0.001)
Gender	0.218***	0.076*	0.110**	0.243***	0.041	0.189***	0.265***	0.029	0.076**
	(0.064)	(0.043)	(0.052)	(0.059)	(0.138)	(0.061)	(0.060)	(0.058)	(0.037)
Household size	0.057***	-0.048***	-0.085***	0.036***	-0.001	0.015	0.031**	0.015	0.035***
	(0.013)	(0.008)	(0.013)	(0.011)	(0.026)	(0.014)	(0.012)	(0.011)	(0.009)
Education	0.111**	0.070**	0.133***	0.117**	0.008	0.129***	0.099**	0.045	0.077**
	(0.050)	(0.032)	(0.038)	(0.051)	(0.091)	(0.049)	(0.049)	(0.040)	(0.031)
Nonfarm	0.176***	0.163***	0.238***	0.176***	-0.041	0.230***	0.167***	0.018	0.172***
	(0.063)	(0.029)	(0.047)	(0.056)	(0.130)	(0.058)	(0.061)	(0.046)	(0.036)
Credit	0.555***	0.083**	0.142	0.470***	-0.059	0.103	0.435***	0.087	0.136*
	(0.087)	(0.042)	(0.119)	(0.114)	(0.215)	(0.126)	(0.088)	(0.075)	(0.071)
Clean water	-0.039	-0.037	0.009	-0.052	-0.066	-0.132*	-0.052	-0.094*	-0.079
	(0.072)	(0.045)	(0.046)	(0.065)	(0.094)	(0.076)	(0.067)	(0.052)	(0.050)
Consolidation	0.362***	0.058	0.059	0.409***	-0.142	0.273***	0.407***	0.027	0.211***
	(0.088)	(0.037)	(0.114)	(0.075)	(0.271)	(0.082)	(0.076)	(0.098)	(0.053)
Farm size	0.255***	0.152***	0.101**	0.246***	0.199*	0.427***	0.235***	0.120***	0.254***
	(0.028)	(0.019)	(0.042)	(0.027)	(0.102)	(0.031)	(0.026)	(0.038)	(0.019)
Irrigation	0.483***	0.025	-0.080	0.489***	-0.146	0.122	0.486***	-0.101	0.075
	(0.080)	(0.042)	(0.103)	(0.079)	(0.210)	(0.099)	(0.075)	(0.078)	(0.061)
South	0.460***	-0.255***	-0.112	0.403***	-0.871***	-0.233***	0.392***	-0.574***	-0.361***
	(0.079)	(0.045)	(0.078)	(0.076)	(0.184)	(0.064)	(0.074)	(0.084)	(0.042)
West	0.955***	-0.017	-0.028	0.949***	-0.783**	-0.137	0.866***	-0.230*	-0.058
	(0.086)	(0.059)	(0.156)	(0.081)	(0.368)	(0.096)	(0.082)	(0.132)	(0.075)
North	1.053***	-0.120**	-0.066	0.982***	-0.914**	-0.101	0.903***	-0.250*	0.158**
	(0.094)	(0.058)	(0.176)	(0.088)	(0.367)	(0.105)	(0.087)	(0.135)	(0.064)
Nonfarm_re	0.299			0.248			0.417		
	(0.282)			(0.266)			(0.256)		
Awareness	0.330***			0.198*			0.271***		
	(0.092)			(0.110)			(0.097)		
Ln(σ_j)		-0.49***	-0.45***		0.39**	0.07***		0.27***	0.43 ***
		(0.033)	(0.031)		(0.207)	(0.014)		(0.123)	(0.034)
ρ_i		0.23*	0.06		-0.81**	0.09		-0.65**	0.15
		(0.123)	(0.406)		(0.299)	(0.054)		(0.263)	(0.094)
Log pseudolikelihood	-5 111.90			-7 958.63			-5 628.84		
Wald test for independence (Chi^2)	3.34**			4.50***			5.57***		

Note: The Eastern Province is considered as reference point. Sample size: 4 090 households. Standard errors clustered at the enumeration area (EA = cluster) level in parentheses. Ln(σj) denotes the log of the square root of the variance of the error terms, ε_{jh}, in the outcome equations (4a) and (4b) respectively; ρ_i denotes the correlation coefficient between the error term, μ_h, of the selection equation (2) and the error term, ε_{jh}, of the outcome equations (4a) and (4b) respectively.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

In addition, the negative and significant coefficients of the household size variable on expenditure per capita specification indicates that the number of household members tends to influence adversely the household expenditure of both adopters and non-adopters. Conversely, the positive coefficients of the household size variable in farm income and farm yield outcome equations show that an increase in the number of household members tends to increase farm income and yield respectively. This is because the farmers use their own family members to work on the farm for both the land preparation and other production processes.

The lower parts of Table 2 show the Wald statistics to test the independence between residuals of the selection and outcome equations. In all cases, the Wald tests lead us to conclude that we cannot reject the alternative hypothesis of dependence between the residuals of the selection and outcome equations. This result is also confirmed by the significance of the estimated correlation coefficients, $\hat{\rho}$, for adopters. Hence, these findings clearly show that there is a selection bias resulting from the existence of unobserved factors in the MAI adoption decision. This is the reason why using switching regression models that can control both observed and unobserved factors would be an ideal best approach in this study. The negative sign of the estimated correlation coefficients (columns (5) and (8) in Table 2) implies the existence of a positive bias, which means that farmers with above average farm income and farm yields are more likely to adopt MAI. This result is consistent with earlier findings by Abdulai and Huffman (2014), but contradicts the findings of Kabunga *et al*. (2012). In Table 2 (column (2)), the equation for the estimated correlation coefficient associated with household consumption per capita was positive and statistically significant only for adopters (ρ_i). This result implies that there is a negative selection bias, indicating that households with below-average consumption per capita have a higher probability of adopting MAI.

It is important to note that statistical non-significance for ρ_i would mean that, in the absence of adoption, there would be no significant differences in the average values of the outcomes resulting from unobservables between the two groups. Further, it can be observed in Table 2 that the estimated correlation coefficient, $\hat{\rho}$, albeit negative, is not significantly different from zero.

5.3 Household welfare effects of MAI adoption

We measured the effect of MAI adoption on household welfare using three outcome indicators (farm income, farm yield, and expenditure per capita level). The predicted values from ESR were used to examine the mean differences between adopters/non-adopters if they had not/had adopted.

The first row under each outcome indicator in Table 3 reports the mean predictions for adopters (a), their counterfactuals (c), and the average treatment effect on the treated (ATT). In all cases, the net ATT results indicate that MAI adoption has positive and significant effects on farm income, farm yield, and expenditure per capita, at 2.4%, 1.4% and 2.5% higher respectively than had they not adopted MAI. The second row under each outcome indicator in Table 3 provides the counterfactual values (d), mean predictions for non-adopters (b), and average treatment effects on the untreated (ATU). In general, the findings show significant and positive effects of MAI adoption on farm income, yield and consumption respectively, which are 25%, 17% and 0.4% higher respectively if the farmers had adopted MAI. This underscores the importance of technology diffusion for an agricultural revolution in the developing world. The findings reaffirm the findings from the existing literature on the effect of farm innovations on raising farm yields and reducing the poverty level among farm households (Zeng *et al*. 2015; Abdulai 2016). In countries such as Rwanda, where more than 83% of households live in rural areas and make use of subsistence farming, the use of such MAI would play a crucial role in ensuring food security.

Table 3: Expected value of MAI adoption for farm yield, farm income and consumption per capita: Treatment and heterogeneity effects on farm household

Sub-samples	MAI adoption decision		Treatment effects	Treatment effect in %
	To adopt	Not to adopt		
	Mean of log farm income			
Household adopted MAI	(a) 10.25 (.0105)	(c) 10.00 (.0107)	ATT = 0.24*** (.0150)	2.4***
Household not adopted MAI	(d) 11.92 (.0138)	(b) 9.53 (.0124)	ATU = 2.39*** (.0186)	25.0***
Heterogeneity effects	BH_1 = -1.67*** (.0171)	BH_2 = 0.47*** (.0163)	THE = -2.15 (.0318)***	
	Mean of log farm yield			
Household adopted	(a) 7.01 (.0072)	(c) 6.91 (.0080)	ATT = 0.10*** (.0107)	1.4***
Household not adopted	(d) 7.58 (.0090)	(b) 6.48 (.0093)	ATU = 1.10*** (.0130)	17.0***
Heterogeneity effects	BH_1 = -0.57*** (.0114)	BH_2 = 0.42*** (.0122)	THE = -1.00 (.0224)***	
	Mean of log consumption per capita			
Household adopted	(a) 9.54 (.0043)	(c) 9.33 (.0047)	ATT = 0.21*** (.0064)	2.5***
Household not adopted	(d) 9.27 (.0054)	(b) 9.22 (.0052)	ATU = 0.04*** (.0075)	0.4***
Heterogeneity effects	BH_1 = 0.27*** (.0068)	BH_2 = 0.11*** (.0070)	THE = 0.25 (.0132)***	

Notes: Standard errors in parentheses. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
The mean outcome values are predictions based on the estimates from the ESR model. As the outcome variables in the ESR equations are expressed in log forms, the predictions are also provided in logs. Converting the means back to kg would lead to inaccuracies (Kabungo *et al*. 2012), resulting from the inequality of arithmetic and geometric means (AM-GM inequality). THE: Transitional heterogeneity effects; BH: Base heterogeneity effects; ATT: Average treatment effects on the treated; ATU: Average treatment effects on the untreated

However, the negative signs of THE on farm income and farm yield are an indication that the effects of adoption are significantly smaller for farm households that actually adopted relative to those that do not adopt. Interestingly, the negative values of BH_1 for the effects of MAI adoption on farm income and farm yield indicate that the effect of MAI adoption on farm income and farm yield is smaller for farmers who did adopt than for those who did not adopt in the counterfactual specification that they adopted. In general, the results show that farm households that adopted MAI are still better off when adopting than not adopting, and the non-adopters are still worse off when not adopting than adopting.

Table 4: Impact of modern agricultural inputs adoption on farm household welfare

Outcome variables	Adopters	Non-adopters	ATE	ATE in %	T-values
Income	10.25	9.53	0.72***	7.5***	44.15
Farm yield	7.01	6.48	0.52***	8.0***	45.09
Consumption	9.54	9.22	0.32***	3.5***	48.12

Notes: *** significant at the 1% level; ATE: Average treatment effects

The estimates for average treatment effects (ATE) showing the effect of MAI adoption on farm income, farm yield, and household expenditure level are provided in Table 4. Unlike the mean differences in Table 1, which simply compares the effect of MAI adoption on outcome indicators based on observed farm and household characteristics, the ATE estimates account for selection bias arising from the fact that adopters and non-adopters may be systematically different. Therefore, Table 4 more specifically provides the causal effect of MAI adoption on farm income, farm yield and consumption per capita, at 7.5%, 8.0% and 3.5% respectively. The findings are also consistent with the existing literature (Abdulai & Huffman 2005; Minten & Barrett 2008; Amare *et al*. 2012; Abdulai & Huffman 2014), which found that new agricultural technology improves farm yields and farm income for smallholder farmers. It also is clear that adopting farm technologies induces a clearly distinguishable pattern between non-adopters and adopters for all the three outcome indicators. This confirms the earlier claim that it is essential to adopt technologies and that they comprise a sine qua non condition for rural farmers to enhance their welfare and allow countries to achieve sustainable development goals one and two.

Finally, another useful difference between adopter and non-adopters is presented in Figure A.1, which compares the actual treatments of (a) and (b) from Table A.1 and their corresponding counterfactual estimates in (c) and (d) of the same table. In all specifications, the distribution density is relatively higher when the farm household adopts MAI. We finally provide nonparametric densities of actual and hypothetical adoption and non-adoption values for outcome equations in Figure A.1 and, in all cases, the adoption decisions seem to improve the farmers' livelihoods.

6. Conclusion and implications

This study examines factors that influence MAI adoption and the effects of adoption on household welfare in rural Rwanda. Farm household data from the EICV3 (2010/2011) were used to derive comparative average values between adopters and non-adopters for farm income expressed in Rwandan francs, farm yield scaled in kilograms per hectare, and per capita consumption valued in local currency. The analysis of descriptive statistics reveals significant differences between farmers who did adopt and those who did not adopt. However, we note that those differences are not sufficient to conclude that adopters of MAI are better off than non-adopters, since the comparison did not account for unobserved characteristics and self-selection bias among farmers. Therefore, factors affecting farmers' adoption decision and subsequent welfare implications were analysed using an ESR model to simultaneously account for both the self-selection problem and unobserved heterogeneity factors affecting farmers' adoption decisions.

Analysing the factors that influence the adoption of MAI reveals useful and interesting results. Variables such as farm credit, farm size endowed by household, and land consolidation practices were found to have a significant positive effect on increasing the probability that a household would adopt MAI. Access to agricultural credit made farmers less liquidity constrained, hence increasing their likelihood to adopt MAI, which subsequently led to potential changes in farm income, yield and consumption levels.

Based on the results, three specific conclusions are formulated: First, the results of the study show that farm households that adopted MAI have different farm and household characteristics than those that did not adopt. These differences are logically identified as the main source of variations in farm household welfare between the two groups. Second, the results furthermore indicate that MAI adoption significantly increased farm income and farm yield and improved household consumption per capita, and eventually reduced the poverty level. The study reveals that farmers who actually adopted are better off than farm household that did not adopt in the counterfactual case that they did not adopt. Therefore, this suggests that farmers who adopted have some unobserved characteristics (like managerial skills, etc.) that helped to increase their production and make them more food secure, irrespective of their MAI adoption policies. Third, and interestingly, the study reveals that the effects of MAI adoption on farm income and farm yield were smaller for farmers who actually did adopt than for farmers who did not adopt in their counterfactual specification that they adopted. From this it seems that, if both groups (adopters and non-adopters) adopted MAI at the same time, the farmers who did not adopt would benefit the most from MAI adoption. Therefore, MAI adoption policies seem to be more important for the non-adopters to improve their low capacity in farm income-generating activities.

From the policy implications, the findings of this study are very useful to improve MAI adoption when farming. The government, together with stakeholders, needs to strengthen access to farm credit by poor people and, where possible, provide substantial subsidies for MAI adoption. One example would be to establish regional seed production centres at the sector or village level. However, most of these policy implications can only be realised at a high cost. The implication of this is that a joint effort is required between the country and development partners, including input from the private sector that would ensure the sustainability of the use of MAI and increase farm yield and income. In the end, improving extension services and disseminating information that improves farmers' awareness of MAI are of paramount importance in terms of addressing economic challenges, such as poverty and food insecurity issues.

References

Abdulai A & Huffman W, 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. Land Economics, 90(1): 26–43.

Abdulai A & Huffman W, 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. American Journal of Agricultural Economics 87(3): 645–59.

Abdulai AN, 2016. Impact of conservation agriculture technology on household welfare in Zambia. Agricultural Economics 47(6): 729–41.

African Seed Traders Association (AFSTA), 2010. Rwanda seed sector baseline study. Available at: https://www.afsta.org/wp-content/uploads/2015/12/RWANDA-SEED-SECTOR-BASELINE-STUDY.pdf

Amare M, Asfaw S & Shiferaw B, 2012. Welfare impacts of maize–pigeonpea intensification in Tanzania. Agricultural Economics 43(1): 27–43.

Asfaw S, Shiferaw B, Simtowe F & Lipper L, 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food Policy 37(3): 283–95.

Barrett CB (ed.), 2013. Food security and sociopolitical stability. Oxford: Oxford University Press.

Barrett CB, Moser CM, McHugh OV & Barison J, 2004. Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. American Journal of Agricultural Economics 86(4): 869–88.

Cantore N, 2011. The crop intensification program in Rwanda: A sustainability analysis. London: Overseas Development Institute.

Chavas J-P & Shi G, 2015. An economic analysis of risk, management and agricultural technology. Journal of Agricultural and Resource Economics 40(1): 63–79.

Carter DW & Milon JW, 2005. Price knowledge in household demand for utility services. Land Economics 81(2): 265–83.

De Janvry A, Fafchamps M & Sadoulet E, 1991. Peasant household behaviour with missing markets: Some paradoxes explained. The Economic Journal 101(409): 1400–17. https://doi.org/10.2307/2234892

Di Falco S, Veronesi M & Yesuf M, 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics 93(3): 825–42.

Dzanku FM, Jirstrom M & Marstop H, 2015. Yield gap-based poverty traps in rural Sub-Saharan Africa. World Development 67: 336–62.

Faltermeier L & Abdulai A, 2009. The impact of water conservation and intensification technologies: Empirical evidence for rice farmers in Ghana. Agricultural Economics 40(3): 365–79.

Grabowski PP, Kerr JM, Haggblade S & Kabwe S, 2016. Determinants of adoption and disadoption of minimum tillage by cotton farmers in eastern Zambia. Agriculture, Ecosystems and Environment 231: 54–67.

Heckman JJ, 1979. Sample selection bias as a specification error. Econometrica 47(1): 153–61.

Jalan J & Ravallion M, 2003. Does piped water reduce diarrhea for children in rural India? Journal of Econometrics 112(1): 153–73.

Jayne TS, Sitko NJ, Mason NM & Skole D, 2018. Input subsidy programs and climate smart agriculture: Current realities and future potential. In Lipper L, McCarthy N, Zilberman D, Asfaw S & Branca G (eds.), Climate smart agriculture: Building resilience to climate change. Cham, Switzerland: Springer

Kabunga NS, Dubois T & Qaim M, 2012. Yield effects of tissue culture bananas in Kenya: Accounting for selection bias and the role of complementary inputs. Journal of Agricultural Economics 63(2): 444–64.

Kassie M, Shiferaw B & Muricho G, 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. World Development 39(10): 1784–95. https://doi.org/10.1016/j.worlddev.2011.04.023

Kelly VA, Mpyisi E, Murekezi A, Neven D & Shingiro E, 2001. Fertilizer consumption in Rwanda: Past trends, future potential, and determinants. Paper prepared for the Policy Workshop on Fertilizer Use and Marketing, organized by MINAGRI and USAID, 22–23 February, Rwanda.

Khonje MG, Manda J, Mkandawire P, Tufa AH & Alene AD, 2018. Adoption and welfare impacts of multiple agricultural technologies: Evidence from eastern Zambia. *Agricultural Economics* 49(5): 599–609.

Lee LF, 1982. Some approaches to the correction of selectivity bias. The Review of Economic Studies 49(3): 355–72.

Lokshin M & Sajaia Z, 2004. Maximum likelihood estimation of endogenous switching regression models. Stata Journal 4: 282–9.

Ma W & Abdulai A, 2016. Does cooperative membership improve household welfare? Evidence from apple farmers in China. Food Policy 58: 94–102.

Maddala G, 1983. Limited-dependent and qualitative variables in econometrics. Cambridge: Cambridge University Press.

Ministry of Agriculture, Rwanda, 2011a. Crop intensification program (CIP): Annual Report. Kigali, Rwanda: Ministry of Agriculture.

Ministry of Agriculture, 2011b. Farm land use consolidation in Rwanda. Assessment from the perspective of the agriculture sector. Kigali, Rwanda: Ministry of Agriculture.

Minten B & Barrett CB, 2008. Agricultural technology, productivity, and poverty in Madagascar. World Development 36(5): 797–22.

Morris M, Kelly VA, Kopicki R & Byerlee D, 2007. Fertilizer use in African agriculture: Lessons learned and good practice guidelines. Washington DC: World Bank Publications.

National Institute of Statistics of Rwanda (NISR), 2015. Seasonal agricultural survey report – 2015. Kigali: NISR.

Nilsson P, 2019. The role of land use consolidation in improving crop yields among farm households in Rwanda. The Journal of Development Studies 55(8): 1726–40.

Nsabimana A, Niyitanga F, Weatherspoon DD & Naseem A, 2021. Land policy and food prices: Evidence from a land consolidation program in Rwanda. Journal of Agricultural & Food Industrial Organization 19(1): 63–73.

Rosenbaum PR & Rubin DB, 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70(1): 41–55. https://doi.org/10.1093/biomet/70.1.41

Sánchez PA, 2010. Tripling crop yields in tropical Africa. Nature Geoscience 3(5):299–300.

Syrovátka M, 2007. Aggregate measures of welfare based on personal consumption. In Environmental economics, policy and international relations: Proceedings of the Sborníkz konference konané, Czech Republic. Available at https://www.development.upol.cz/uploads/dokumenty/Syrovatka_aggregate_measures_of_welfare.pdf

Tesfaye W, Blalock G & Tirivayi N, 2019. Climate-smart agricultural innovations and rural poverty in Ethiopia. *American Journal of Agricultural Economics* 103(3): 878–99.

Winters P, Maffioli A & Salazar L, 2011. Introduction to the special feature: Evaluating the impact of agricultural projects in developing countries. Journal of Agricultural Economics 62: 393–402.

Wooldridge JM, 2002. Introductory econometrics: A modern approach. Mason, OH: Thomson South-Western.
World Bank, 2011. Rwanda economic update, April 2011: Seeds for higher growth. Washington DC: World Bank.
Zeng D, Alwang J, Norton GW, Shiferaw B, Jaleta M & Yirga C, 2015. Ex post impacts of improved maize varieties on poverty in rural Ethiopia. Agricultural Economics 46(4): 515–26.

Appendices

Appendix 1: Endogeneity and adoption decision

The issue to be addressed with care when evaluating adoption decisions and welfare implications is endogeneity. Specifically, farmers may devote more labour to farm activities during the farming season, including MAI adoption, and less labour to off-farm businesses. In this situation, therefore, the non-farm business is determined jointly with the MAI adoption decision. To deal with this type of endogeneity, the approach proposed by Abdulai and Huffman (2014) was used here. In the first stage, non-farm business was estimated separately as a function of all other exogenous variables used in the adoption equation (2). In the second stage, the derived residuals were included in the selection equations. By doing this, the probit estimates of the potential endogenous variables in explanatory variables became consistent (Wooldridge 2002). Furthermore, two variables – awareness and non-farm business residuals – define the exclusion restriction when estimating ESR.

Appendix 2: Conditional expectations, average treatment and heterogeneity effects

We used the estimates from the ESR model to derive the expected farm income, farm yield and equivalised per capita of farm households. These estimates were used to compare the expected outcomes of adopters of MAI (a) with respect to non-adopters (b) and to examine the expected farm yield, farm income and state of consumption expenditure in the hypothetical cases that the adopters did not adopt (c) and that the non-adopters would have adopted (d). The four cases of the expected outcome values are presented in Table A.1 and are expressed as follows:

$$E(y_{1h} \mid L_h = 1) = Z_{1h}\beta_1 + \sigma_{1\mu}\lambda_{1h} \tag{A.1a}$$

$$E(y_{2h} \mid L_h = 0) = Z_{2h}\beta_2 + \sigma_{2\mu}\lambda_{2h} \tag{A.1b}$$

$$E(y_{2h} \mid L_h = 1) = Z_{1h}\beta_2 + \sigma_{2\mu}\lambda_{1h} \tag{A.1c}$$

$$E(y_{1h} \mid L_h = 0) = Z_{2h}\beta_1 + \sigma_{1\mu}\lambda_{2h} \tag{A.1d}$$

The cases (1a) and (1b), on the diagonal in Table A.1, represent the actual expectations observed in the sample, while (1c) and (1d) represent the counterfactual expected values. Furthermore, the effects of treatment on the adoption of MAI (ATT) were calculated as the difference between (1a) and (1c):

$$ATT = E(y_{1h} \mid L_h = 1) - E(y_{2h} \mid L_h = 1)$$
$$= Z_{1h}(\beta_1 - \beta_2) + (\sigma_{1\mu} - \sigma_{2\mu})\lambda_{1h} \tag{A.2}$$

This represents the effect of MAI on the welfare of small-scale farming households that have adopted the techniques. In a similar fashion, the effect of non-treatment (ATU) for the farm households that did not adopt MAI was calculated as the difference between (1d) and (1b):

$$ATU = E(y_{1h} \mid L_h = 0) - E(y_{2h} \mid L_h = 0)$$
$$= Z_{2h}(\beta_1 - \beta_2) + (\sigma_{1\mu} - \sigma_{2\mu})\lambda_{2h} \tag{A.3}$$

The diagonal cases (1a) and (1b) were used to compute the average treatment effect (ATE) between actual adopted and non-adopted farm households, noting that this treatment effect captures the average benefit associated with the MAI adoption decision conditional on $\mathbf{Z}_{jh}$ for $j = 1, 2$. The difference between (A.1a) and (A.1b) therefore leads to:

$$ATE = E(y_{1h} \mid L_h = 1) - E(y_{2h} \mid L_h = 0)$$
$$= (Z_{1h}\beta_1 - Z_{2h}\beta_2) + (\sigma_{1\mu}\lambda_{1h} - \sigma_{2\mu}\lambda_{2h}) \tag{A.4}$$

Moreover, the expected outcomes from equations (A.1a) to (A.1d) were used to estimate the heterogeneity effects (unobserved effects). For instance, farm households that adopted MAI may have gained more than farm households that did not adopt, not due to the fact that they decided to adopt, but owing to unobserved factors such as farm management skills. Following Carter and Milon (2005) and Asfaw et al. (2012), the effects of base heterogeneity for the group of farmers who adopted was defined as the difference between (1a) and (1d):

$$BHE_1 = E(y_{1h} | L_h = 1) - E(y_{1h} | L_h = 0)$$
$$= (Z_{1h} - Z_{2h})\beta_1 + (\lambda_{1h} - \lambda_{2h})\sigma_{1\mu} \tag{A.5}$$

Similarly, for the group of farm households that did not adopt MAI, the base heterogeneity effects were defined as the difference between (1c) and (1b):

$$BHE_2 = E(y_{2h} | L_h = 1) - E(y_{2h} | L_h = 0)$$
$$= (Z_{1h} - Z_{2h})\beta_2 + (\lambda_{1h} - \lambda_{2h})\sigma_{2\mu} \tag{A.6}$$

The final step was to examine whether the effects of adopting MAI was larger or smaller for the farm households that actually adopted or for the non-adopters in the counterfactual cases that they did adopt. These transitional heterogeneity effects (THE) were defined as the difference between equations (A.2) and (A.3):

$$THE = (Z_{1h} - Z_{2h})(\beta_1 - \beta_2) + (\lambda_{1h} - \lambda_{2h})(\sigma_{1\mu} - \sigma_{2\mu}) \tag{A.7}$$

Appendix 3: Description of the calculation of farm household welfare

Table A.1 explains how we computed the changes in farm household welfare based on the actual and hypothetical scenario for adopters and nonadopters of MAI in Rwanda.

Table A.1: Derivation of average expected values, treatment and heterogeneity effects

Sample categories	Decision stage		Treatment effects
	Adopted	Not adopted	
Adopter farm households	(1a) $E(y_{1h} / L_h = 1)$	(1c) $E(y_{2h} / L_h = 1)$	ATT
Non-adopter farm households	(1d) $E(y_{1h} / L_h = 0)$	(1b) $E(y_{2h} / L_h = 0)$	ATU
Heterogeneity effects	BHE_1	BHE_2	THE

Notes: Table form adapted from Di Falco *et al*. (2011). Points (1a) and (1b) represent expected farm yield and farm income, while (1c) and (1d) are counterfactuals of farm yield and farm income of small-scale households.

Table A.2: Falsification test for the validity of the selected instruments in our SER model

Variables	**Adopt (0/1)**	**Farm income**	**Adopt (0/1)**	**Farm yield**	**Adopt (0/1)**	**Consumption per capita**
Age	-0.010***	-0.004**	-0.010***	-0.001	-0.010***	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Gender	0.259***	0.212***	0.259***	0.103***	0.259***	0.096***
	(0.057)	(0.051)	(0.057)	(0.028)	(0.057)	(0.029)
Household size	0.032***	0.024**	0.032***	0.033***	0.032***	-0.062***
	(0.012)	(0.011)	(0.012)	(0.006)	(0.012)	(0.006)
Education	0.144***	0.126***	0.144***	0.084***	0.144***	0.103***
	(0.046)	(0.040)	(0.046)	(0.024)	(0.046)	(0.024)
Nonfarm	0.189***	0.199***	0.189***	0.130***	0.189***	0.194***
	(0.058)	(0.051)	(0.058)	(0.030)	(0.058)	(0.027)
Credit	0.562***	0.257***	0.562***	0.206***	0.562***	0.107***
	(0.081)	(0.066)	(0.081)	(0.040)	(0.081)	(0.035)
Clean water	-0.048	-0.126**	-0.048	-0.096***	-0.048	-0.024
	(0.063)	(0.057)	(0.063)	(0.037)	(0.063)	(0.034)
Consolidation	0.412***	0.405***	0.412***	0.264***	0.412***	0.077**
	(0.078)	(0.064)	(0.078)	(0.039)	(0.078)	(0.037)
Farm size	0.253***	0.419***	0.253***	0.234***	0.253***	0.139***
	(0.025)	(0.024)	(0.025)	(0.015)	(0.025)	(0.013)
Irrigation practice	0.467***	0.209***	0.467***	0.075*	0.467***	0.013
	(0.075)	(0.066)	(0.075)	(0.039)	(0.075)	(0.032)
South Province	0.369***	-0.353***	0.369***	-0.382***	0.369***	-0.148***
	(0.074)	(0.058)	(0.074)	(0.035)	(0.074)	(0.031)
West Province	0.927***	-0.017	0.927***	0.045	0.927***	0.038
	(0.080)	(0.076)	(0.080)	(0.049)	(0.080)	(0.038)
North Province	0.969***	-0.102	0.969***	0.110**	0.969***	-0.046
	(0.087)	(0.076)	(0.087)	(0.044)	(0.087)	(0.038)
Nonfarm _re	0.427*	-0.110	0.427*	0.036	0.427*	0.062
	(0.246)	(0.205)	(0.246)	(0.123)	(0.246)	(0.121)
Awareness	0.294***	-0.109	0.294***	-0.020	0.294***	0.003
	(0.083)	(0.070)	(0.083)	(0.042)	(0.083)	(0.037)
Constant	-1.897***	8.188***	-1.897***	5.632***	-1.897***	8.993***
	(0.171)	(0.137)	(0.171)	(0.087)	(0.171)	(0.084)
Wald test for nonfarm_re (Chi^2)	3.01*					
Wald test for awareness (Chi^2)	12.7***					
F-test for nonfarm_re		0.28				
F-test for awareness		2.42				
Observations	4,090	3,771	4,090	3,599	4,090	3,439
R-squared		0.201		0.287		0.108

Note: The Eastern Province was considered as reference point. Sample size: 4 090 households. Standard errors clustered at the enumeration area (EA = cluster) level in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Adoption is estimated by the probit model, while the outcome indicators are implemented using the ordinary least square model.

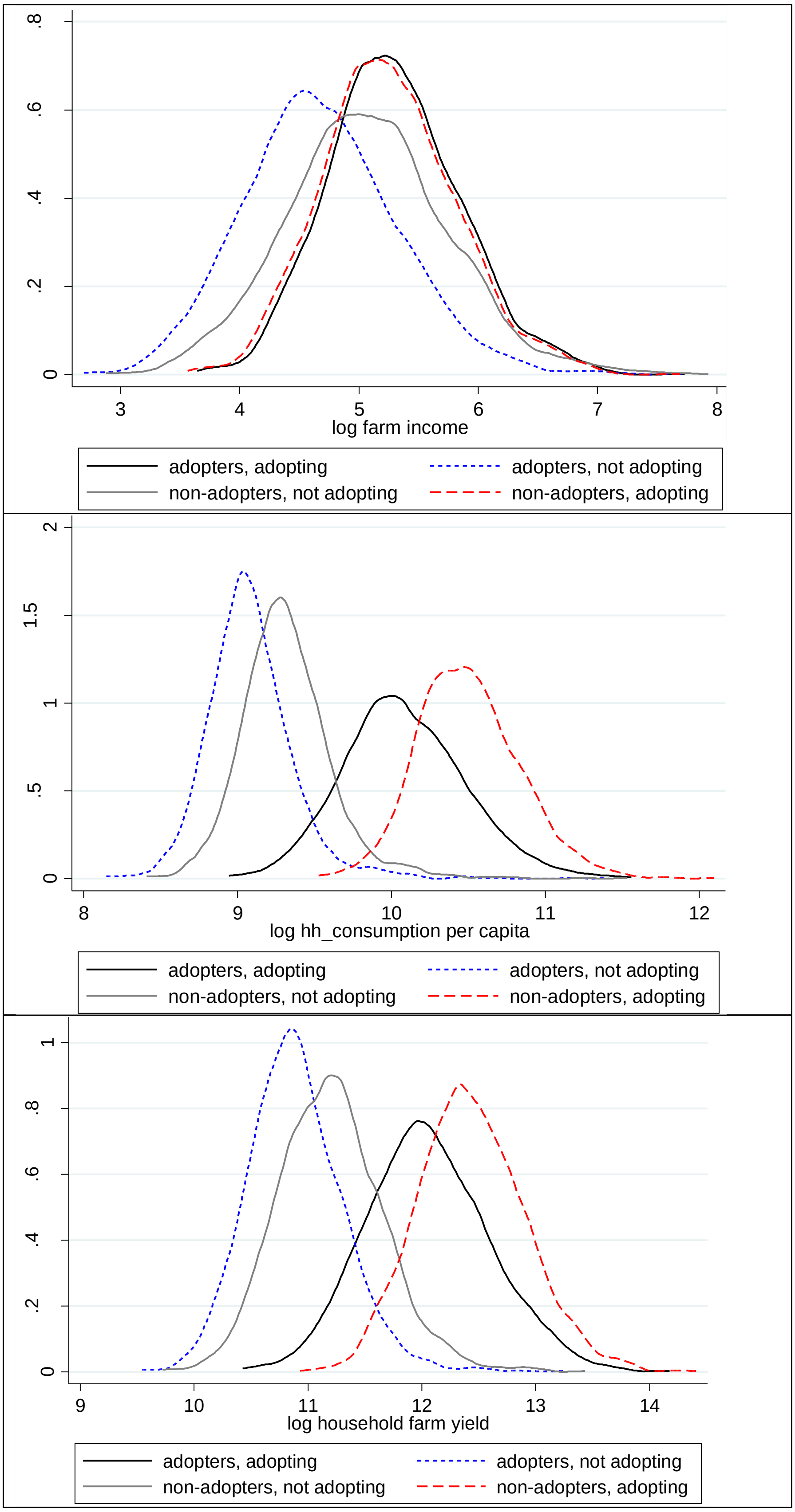

Figure A1: Nonparametric densities of actual and counterfactual adoption and non-adoption values for the outcome equations