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Heterogeneous effects from integrated farm innovations on welfare in Rwanda

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ABSTRACT

Using a multinomial endogenous switching regression model, this study examined the factors that influence farmers' decisions to adopt multiple integrated technologies and then estimated the effects of adopting integrated farm technologies on farm yield, farm income, and household food expenditure. The results showed that adopting higher-order suites of technologies provides higher dividends to farmers in terms of farm yield and income relative to a single technology adoption. Among different integrated technologies, the study found that the technology mix involving crop and soil innovations exerts the greatest impact. Further findings from the study, however, shows that there are no statistical differences in food expenditure from adopting higher-order packages of technologies, albeit the impacts being positive. This could explain the diversion of additional gains obtained towards investing in family assets, child education, and health expenditures. In addition, the study suggests that the level of education of the family head and access to credit significantly influence the decision to adopt multiple integrated technologies. The study provides suggestive evidence for a shift in policy design for the country's farm productivity coupled with investment policies that promote access to credit and education, especially among rural communities.

1. Introduction

Increasing agricultural productivity is key to solving the problems of food insecurity, trade balance poverty, and youth unemployment in Sub-Saharan Africa [SSA] (Adom & Adams, 2020; Adom et al., 2018; African Development Bank, 2016; Thornton et al., 2011; United Nations, 2010). Given that productivity levels comparatively remain very low in the region (Pardey et al., 2016; Adom et al., 2018) and considering the pressures from urbanization and population growth (African Development Bank, 2016; Djurfeldt & Jirström, 2013), there is need for local economies to adopt innovative ways to ensure sustainable structural economic transformation.

Among other things, there is a view that using modern farm technologies can lead to improved farm productivity (Tesfaye et al., 2019; Khonje et al., 2018) and put the region on a sustainable path to development. This is because the extant literature has found that using agricultural technologies can help to deal with farm risks associated with climate change (Chavas & Shi, 2015) and the rain-fed dependent nature of production in the sector (Dzanku et al., 2015; Tesfaye et al., 2019). Consequent to that, several empirical studies have considered the welfare implications of adopting improved crop varieties in the agricultural sector such as adopting improved maize varieties (Manda et al., 2016; Zeng et al., 2015; Zeng et al., 2017; Bezu et al., 2014, inter alia), improved leguminous crops (Manda et al., 2019; Asfaw et al., 2012), improved cassava (Wossen et al., 2019), and improved oilseeds and cash crop, and fertiliser (Danso-Abbeam and Baiyegunhi, 2019; Kassie et al., 2011). Other studies such as Abdulai (2016), Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria (2013) and Jaleta et al. (2016) assessed the welfare impact of adopting conservation agricultural practices and minimum tillage. Generally, these studies come to the conclusion that adopting technologies improve the welfare of rural farmers. Adopting improved crop varieties could be seen as a climate-resilient strategy (Fisher et al., 2015) while the use of conservation agricultural practices offers benefits in the form of guaranteed long-term productivity growth and environmental benefits (Jaleta et al., 2016).

To achieve optimal returns from farming, appropriate policies aimed

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at increased productivity growth requires greater use of farm technology (Khonje et al., 2018). While Becerril & Abdulai (2010) further argue that the using multiple integrated innovations (MII)[1] should involve a bundle (or integration) of innovations instead of a single technology; Stevenson et al. (2019) underscore the new evidence of low adoption from several developing countries and suggests that on-farm natural resource management practices contributes to significant constraints to technology adoption. Furthermore, as noted by Aldana et al. (2011) and Leathers and Smale (1991), farmers rarely adopt single innovation but rather complementary technologies in a sequential manner, which should be factored in when assessing the impact of technology adoption. More often, comparisons find that using farm technologies by African farmers is as less as 10–20 percent of those in Europe, America, and Asia. This gap is mostly attributed to the market-based factors (Burke et al., 2017). Motivated by this, the current study uses two rounds of farm household surveys in Rwanda and apply a multinomial endogenous switching regression model to examine the welfare implications of multiple integrated technology use on maize and beans productivity.[2]

Previous studies on the welfare impacts of adopting multiple integrated technologies have relied on either cross-sectional data (e.g. Kassie et al., 2015; Abdualai, 2016; Manda et al., 2016; Teklewold et al., 2013, inter alia) or panel-based data (e,g, Khonje et al., 2018; Kassie et al., 2018; Tesfaye et al., 2019). However, the use of cross-sectional data makes it difficult to derive change in adoption resulting from possible changes in factor prices, returns, livelihood preferences, an idiosyncratic shock among others. Moreover, studies relying on cross-sectional data are limited in addressing effectively self-selection bias and endogeneity problems that might result from both observed and unobserved heterogeneity bias. These concerns are well addressed when using panel data. Therefore, like previous studies such as Khonje et al. (2018), Tesfaye et al. (2019), and Kassie et al. (2018), the current study provides a relatively strong basis for any attribution claim. First, heterogeneous characteristics of technology adopters and non-adopters are potential sources of self-selection bias that could affect the attribution claim. Moreover, confounding factors such as endogenous placement could also weaken the attribution claim. Unlike identification strategies such as the instrumental variable approach and propensity score matching techniques adopted in other studies that are able to handle either unobserved or observed heterogeneity bias, the use of the multinomial endogenous switching regression model in this study reduces the self-selection bias and improves the attribution claim by addressing both unobserved and observed heterogeneity bias.

This study explores these methods in a different context than prior studies, both in terms of the type of crops considered (Maize and beans) and the technology bundle mix.[3] As noted by Straub (2017), "technology adoption is a complex, inherently social, developmental process; individuals construct unique yet malleable perceptions of technology that influence their adoption decisions. Thus, successfully facilitating technology adoption must address cognitive, emotional, and contextual (local) challenges". Existing literature views the use of farm technologies as the main optimal mechanism for improving productivity & and food security, reducing poverty, and providing resilience to farm households (Asfaw et al., 2012). The increased use of technologies can eventually allow farmers to endow household assets and dividends from farming, hence enhancing household ability to cope with shocks. Conducting this study in SSA, specifically in Rwanda, offers a novel contribution to understanding the demand constraints and welfare implications of integrating farm input packages. Over the last two decades, Rwanda has implemented different agricultural policies that intend to transform the agricultural sector to become more competitive and market oriented. National programs such as land use consolidation, girinka, and crop intensification programs have been designed to respond to the broader country's ambitions to increase productivity through high technology adoption and expanding the value addition of farm produce (Nsabimana et al., 2023). Furthermore, those policies aimed at reducing poverty and food insecurity in the country. This study explores whether such policies have contributed to the integration of farm input uptakes by farmers in the country and how this could lead to welfare changes among farm households. The rest of the paper is organised as follows: Section 2 provides the context of farming and technology integration in Rwanda. Section 3 gives data sources and descriptive statistics while section 4 presents theoretical model and estimation techniques employed. Section 5 presents and discusses the results while the last section contains some concluding remarks.

2. Context

Rwanda farm productivity is beset by several challenges. Some of the include the following: (i) High population density on very limited land resource, where the country is among the world densely populated country with 533 pop/ KM-square.[4] This excessive population density has induced shortage of arable land and a decreasing farm size. This has also led to land fragmentation and continued intensive cultivation of land with no fallow. (ii) Soil erosion and climate related threats. The most part country landscape is hilly and steeper slope, and the farming is usually undertaken on the slopes of hills and mountains. Together with excessive deforestation, Rwanda has been experiencing extensive land degradation and soil erosion. (iii) The country's economy is predominantly dependent on agriculture for livelihood, especially for rural household that essentially rely on small scale farming for daily subsistence. This pauses a food insecurity and poverty challenges in the country, where some recent evident show that more than 38 percent of country's population remains under poverty line while 20 percent of the population is food insecure.[5]

Agricultural policies in Rwanda are implemented under crop intensification programmes (CIP), with the aim of sustainably improving farm productivity through procuring improved seeds, fertilisers and pesticides for farmers to increase crop production potentials (Cantore, 2011). Some of the existing literature (Nilsson, 2019; Nsabimana et al., 2021; Del Prete et al., 2019; Bizoza, 2021) have so far examined policy implications of the CIP among Rwanda households. For instance, Nilsson (2019) evaluated the role of CIP on farm productivity among smallholder farmers in Rwanda and finds a positive linkage between CIP and crop yields, but only among farm households with landholdings greater than one hectare in the country.[6] Nsabimana et al (2021) found that the CIP policy was not associated with price differences between intensive and non-intensive monocropped zones on the CIP priority crops. Their

[1] In this study, the terms multiple integrated innovations (MIIs) and Integrated farm innovations (IFIs) have been used interchangeably to refer to the set of agricultural technologies, inputs uptakes, and management practices (packages) that farmers combine while farming.

[2] Although the study uses data that was collected ten years ago, we still believe that the findings from this study remain useful, at least in the context of a country like Rwanda, where more than 70 percent of household livelihood remains dependent on agriculture while poverty and food insecurity are of great concerns in the country.

[3] Crop innovations (i.e. hybrid seeds and Pole beans), input innovations (i.e. fertilisers and pesticides), and soil innovations (i.e. irrigation, drainages, and land terracing).

[4] According to the World Bank, 2021: https://data.worldbank.org/indicator/EN.POP.DNST?locations=RW.

[5] More details on food and livelihood in Rwanda can be accessed in the following report by the World Food Program (WFP), 2022: https://www.wfp.org/countries/rwanda.

[6] . It is important to mention that the majority of farm households own small and few plots of arable land in Rwanda. For instance, according to the EICV 2013/14, the average household land size is 0.55ha, while only 14 percent of households possess at least one hectare of arable land.

findings also show that the policy was likely to widen price gaps of stapple food of non-CIP priority crops in monocropped zones. Del Prete et al. (2019) showed that CIP had ambiguous consumption effects, as it positively impacted the consumption of roots and tubers, but induced a negative effect on meat, fish and fruits consumption. The study identified four channels under which CIP can induce changes in household consumption. First, the changes in farm production can improve the quality, diversity, and quantity of food retained by farm households for their own consumption. Second, agriculture is a source of income from the sale of farm produce. The household uses the sales revenues to buy other nutrition-relevant items. Thirdly, farming is a moderator of household members' time use and gendered decision-making related to household cropping and spending strategies. The fourth channel is that agriculture is the moderator of food demand and supply, hence the availability and relative prices of foods.

In an effort to boost technology adoption among small-scale farmers, several national policies and programs have been implemented in Rwanda, e.g. National Seed Policy in 2007 (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 potentials (beans, potatoes, maize among others), thus ensuring food security and self-sufficiency (Ministry of Agriculture, 2011). Besides, agriculture is still the main sector of economic growth in Rwanda, where it employs approximately 75 % of the total labour force and generates more than 43 per cent of the country's export revenues.[7] Despite significant interventions by government and stakeholders, the number of farmers using these farm technologies is still trivial. For instance, in 2017, the National Institute of Statistics Rwanda (NISR) showed that only 24.48 % of farmers used improved seeds, while the use of inorganic and organic fertilisers was only 11.28 and of 33.03 % respectively, during cropping season B in 2017(NISR, 2017).[8]

The use of modern inputs is also unimpressive in large-scale farming, where improved seeds were used by 40 % while organic and inorganic fertilisers were used by 42.3 and 51.5 % of farmers, respectively, during the season B. In this study, a farmer is considered to have adopted integrated agricultural innovations if he/she had used at least two or more of the selected inputs, fertilizers or soil innovations over 12 months prior to the survey, otherwise, the farmer is regarded a non-adopter. And so, we considered some of the following possible combinations: Crop innovations (hybrid seeds and Pole beans), input innovations (i.e. fertilisers and pesticides), and soil innovations (i.e. irrigation, drainages, and land terracing).

3. Data source and descriptive analysis

The data used in this study was extracted from two waves from Third and fourth Integrated Household Living Conditions Survey of Rwanda (EICV3 and EICV4), respectively, conducted in 2010/2011 and 2013/2014 by National Institute of Statistics for Rwanda (NISR) with financial and technical supports from DFID and European Union (EU). The surveys encompass the entire country in all five provinces, including rural household from Kigali, with South, West, North, East, and provinces each respectively accounts for 19 %, 12 % and 25 % of sampled farm households while rural farm household in Kigali accounts for 7 % of the sample.[9] The sample is restricted to smallholder households with farm activities to ensure that all households in adopt and non-adopt groups had engaged in farm economic activities in 12 months before each survey round was conducted (in Table 1). From 2010/11 household survey, there are 2108 households that were again revisited in EICV4 (2013/14), hence making it possible to have a panel data.[10] Note that the data for the panel subsample from the EICV5 conducted in 2015/16 is not publicly available. It is also noteworthy to mention that although the EICV 5 contains 2427 panel households, unfortunately we could not find it in publicly available data, hence the reason why we stick using the EICV 3&4 where the panel data can be retrieved from shared NISR public household surveys dataset. The definitions of all variables that are used in this study are provided in Table A1 in the appendix. In Table 1, we provide the average values of the outcome variables that were considered under this study. These include annual maize and pole beans farm yields, both expressed in kilograms per ha.[11] Also, we report information on household farm income and food consumption per capita both expressed in local currency (Rwandan francs). The farm income is perceived as agricultural total revenues and farm yield (maize and pole beans) represents the total annual farm produce per smallholder farmers (expressed in kilograms) that each farm household reported as total harvested outputs in entire all crop seasons in a given year. Using farm yields and farm income variables provide relevant indicators on farmer's production performance among smallholder farmers in Rwanda. Household food consumption per capita is computed using total household food expenditure and household size, reflecting the degree of food consumption among smallholder farmers.[12] In this respect, while assessing the utility level between IFI adopters and non-adopters, we use equivalised food consumption per capita by household members as suggested by Syrovátka (2007).

This study uses 1132 household observations that were surveyed in both rounds.[13] The study considers three treatment indicators to measure the impact of IFI adoption on farmers' welfare as shown in Table 1. These include input, crop, and soil innovations. The input innovations include the use of fertilizers, both organic and chemical fertilizer, as well as pesticides during the farming process. In this respect, we consider the farmer as adopter if he/she has used at least one, two or three from organic, inorganic and pesticides. Crop innovations involves the use of hybrids of maize and/or improved seeds of pole beans.[14] The soil innovations involve the farmers that, during farming, have adopted radical terracing, Soil conservation practices and mulching through

[7] Although the study uses data collected ten years back, we would like to mention that the share of the labor force in agriculture did not change substantially. For example, according to the NISR, the total labor force employed in agriculture was around 72 percent of the total labor force in the country (NISR-2022 LFS, Q1).

[8] Rwanda has three main agricultural seasons (A, B and C). Season A runs from September to January and season B from February to May and both A and B are rainy seasons. The quantity of rainfall that occurs has direct impacts on crop production, and hence on food market prices. Season C runs between June and 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.

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

[10] Based on EICV 4 (2013/14), we were able to extract around 1132 smallholder farmers from EICV3 (2010/11). Source: National Institute of Statistics for Rwanda (2015): Integrated Household Living Conditions Survey Main Indicators Report August 2015 [EICV] 2013/14.

[11] It is worth mentioning that the two mean values from both waves present high standard deviations and an indication of possible high variances between farm yields between the two waves.

[12] In computing farm household food expenditure, we take into consideration both all market food purchase transactions by farm households and the total values of their subsistence farming.

[13] In this study, we focus on small-scale farmers. We defined the small farmers as those reported on the dataset having arable land of less or equal to 2 ha. Out of 1599 rural households that made the panel dataset, there were 312 farmers that own more than 2 ha and 155 with incomplete information on all variables of interest in the study. After cleaning and removing those with incomplete information, we remain with enough sample that has limited attrition bias (around 10 percent).

[14] It is important to note that beans and maize are the two principal food staples that are largely produced and consumed by the majority of Rwandans.

Table 1
Distribution of farm and household attributes from the two waves.

	2010: Wave 1		2014: Wave 2		Full sample	
	Mean	Sta.dev	Mean	Sta.dev	Mean	Sta.dev
Outcome variables						
Maize yield (Kg/ha)	588	2080	278	782	433	1579
Beans (Kg/ha)	1174	7237	161	363	667	5147
Farm income (Frws)	55,757	115,685	206,604	381,603	131,181	283,524
Food consumption pc(Frws)	390,709	560,012	604,467	516,832	497,588	549,240
Treatment variables						
Input innovations (1/0)	0.30	0.46	0.46	0.50	0.38	0.48
Crop innovations (1/0)	0.19	0.39	0.27	0.44	0.23	0.42
Soil innovations (1/0)	0.21	0.41	0.30	0.46	0.26	0.44
Farm and household attributes						
Age of household head	45.83	15.49	46.27	16.52	46.05	16.01
Household size	4.88	2.26	4.62	2.16	4.75	2.22
Gender of hh head (1/0)	0.30	0.46	0.30	0.46	0.30	0.46
Education of hh head	0.73	0.44	0.73	0.44	0.73	0.44
Salary/wave in hh (1/0)	0.45	0.50	0.45	0.50	0.45	0.50
Hh is part of VUP (1/0)	0.03	0.18	0.50	0.50	0.27	0.44
Awareness of agr. policies	0.29	0.45	0.32	0.47	0.30	0.46
Cooperative member (1/0)	0.62	0.48	0.77	0.42	0.71	0.45
Household land size (ha)	0.58	1.99	0.67	0.92	0.63	1.55
Have livestocks (1/0)	16.63	8.84	12.81	11.63	14.42	10.71
Hh has farm loan (1/0)	0.04	0.19	0.03	0.18	0.04	0.19
Number of cattle in hh	0.39	0.49	0.67	0.47	0.55	0.50
Non-farm business(1/0)	0.36	0.48	0.41	0.49	0.39	0.49
Observations	1132		1132		2264	

Notes: The data are derived from EICV3 (2010) and EICV4 (2014) of sampled rural farmers. Sta.dev stands for the standard deviation, Frws represents the Rwandan francs. Noting that average exchange rate in 2010/2011 was:1 $=604 Frws and in 2013/2014 the average exchange rate was: 1$=669 Frws.

either land consolidation approach or other types of soil preservations such as radical terracing. We also considers farmers that practices irrigation and drainage to be soil innovation adopters.

Further, in Table 1, we also report key control variables used in this study. The table provides basic statistical comparison across the two rounds of surveys of farm households. The household and farm characteristics we consider include age of household head, household size, gender of household head, and education level of household head, land area (expressed in hectares) owned by farm household, a dummy defining farm household with farm credits, off-farm business, and the number of livestock raised by farm households among others. The table also contains information on the cooperative memberships by farm households and the knowledge about the agricultural policies, including the use of improved seeds and other farm innovations. As reported in the table, the majority of the farm household (around 71 % of surveyed smallholder farmers) in Rwanda have been involved in one or more farm cooperatives or any other farm associations. Furthermore, we have also provided the information on integrated farm innovations and the level of adoption across the two waves (as provided in Fig. 1 & 2). Fig. 1 shows the distribution of of integrating farm innovations (IFI) by smallholder farmers in Rwanda. The figure indicates that between the two surveys the adopting, at least, any farm innovation has gone up by 15 percent.

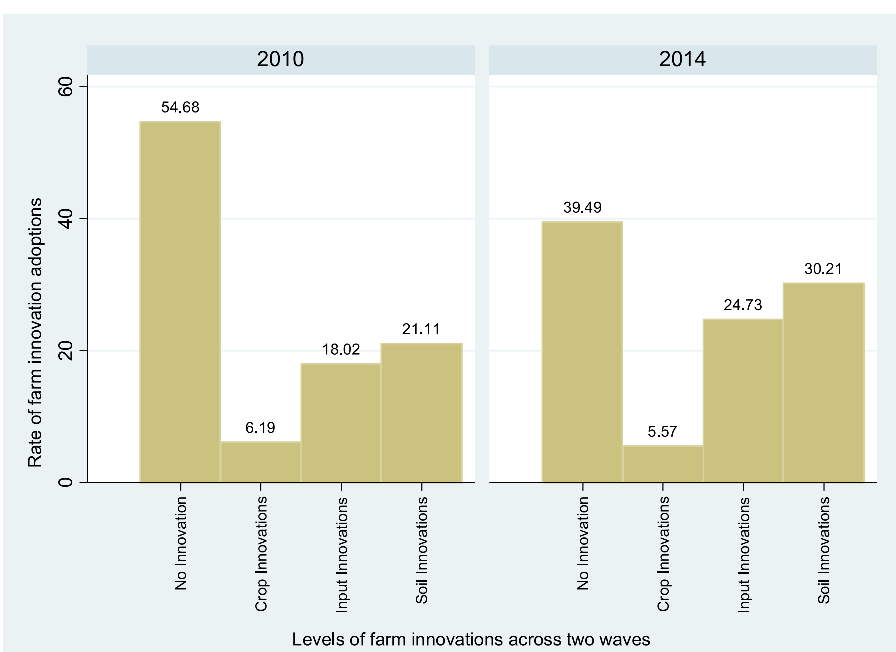

Fig. 1. Distribution of integrating farm innovations (IFI).

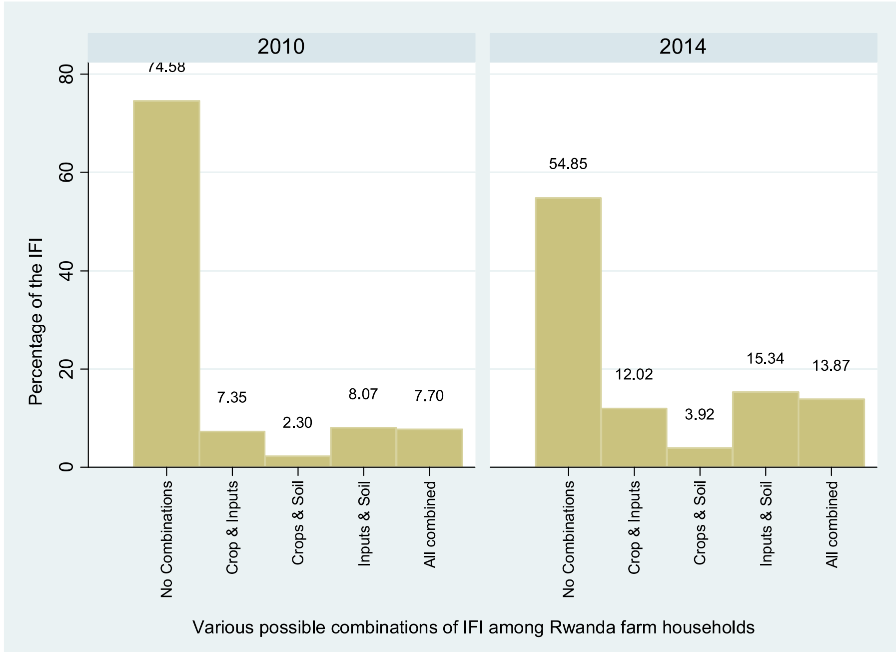

Fig. 2. Distribution of possible farm innovations across the two waves.

This implies significant adoption of farm innovations by farmers in the country. Fig. 2 indicates the distribution of possible integrated farm innovations across the two waves. For instance, in 2010, Fig. 2 shows that around 74 % of farm household did not adopt any integrated innovations during farming but the rate has gone down to 54 % in 2013, implying that 20 percent of farmers have substantially integrated innovations in 2013/14 relative to 2010/11 surveys. The figure reported significant number of farmers combined three possible farm innovation and the combination of farm innovations have increased steadily from 7.7 to 14 percent between 2010/11 and 2013/14, respectively. Other different combinations also show the shifts in uptakes of farm innovations by farmers in the country.

Finally, we also report how smallholder farmers in Rwanda use agricultural innovations in Fig. A1. Along the two waves, the adoption of farm innovation have increased substantially. For instance, in 2010, the figure shows that around 61 % of farm household did not adopt any innovations during farming but the rate has gone down to 47 % in 2014, implying that farmers have improved their adoption rate of agricultural innovations during the course of farming.

4. Methodology and estimation techniques

4.1. Adoption decision and selection bias

Examining the effects of adopting farm innovations on household welfare should account for unobserved heterogeneity and any potential selection bias. The latter is the main issue when evaluating the household adoption decisions and impacts analysis using nonrandomized observational data. When the selection process takes into account time-invariant unobserved heterogeneity, a panel estimator would be strong enough to deal with selectivity issue without using instrument variables (Wooldridge, 2002). In most cases, however, the selection process is implemented based on the time-varying unobserved factors that may influence the outcomes (Wooldridge, 2002; Kessie et al, 2018). In this instance, having the panel data alone cannot guarantee an unbiased estimate of the impact of various sets of farm innovations on welfare outcomes of interest. To deal with such challenge, we estimate a model that combines panel data together with Endogenous Switching Regression (ESR), accounting for the time-varying unobserved factors.

The ESR model has some advantages over other techniques, like propensity score matching (PSM). First, ESR controls for selection bias for unobserved heterogeneity. The ESR model further allows interacting estimates from separate regressions for adopters and non-adopters (Kessie et al, 2018). In addition, unlike other method such as PSM, the use of ESR model enables one to design a counterfactual based on returns (parameter estimates) for attributes of adopters and non-adopters. This implies that the mean values of farm/ household attributes could be similar for adopters and non-adopters, but they may be different in terms of their parameter estimates, which have implications on adoption and yield. For instance, the mean value of the number of plots per farm household could be the same, but the returns (parameter estimates) can be significantly different based on the plot locations and land gradients.

Estimating ESR model of IFI involves a two-stage simultaneous process. In the first stage, farmer's alternative choices in adopting IFI (as reported in Fig. 1) is estimated based on Multinomial logit model (MNLM) that accounts for unobserved factors. Based on the estimated probabilities in MNLM, the Inverse Mills Ratios (IMRs) are computed. In the second stage, we derive the impact of each IFI by estimating Ordinary Least Square (OLS) augmented by IMRs in regression to deal with selection bias resulted from time-varying unobserved factors. Example studies that have adopted similar approach includes the studies by Kessie et al. (2015), Abdulai & Huffman (2014), Di Falco & Veronesi (2013), and Di Falco et al. (2011).

In this study, we follow the approach by Kabunga et al. (2012) and Kessie et al. (2015), where we assume that farmers' choice decision to adopt any IFI choice can be represented by the random utility framework. Adopting IFI includes five possible farm innovation choices, $j(j = 0,1 \ldots 4)$, with $j = 0$ signifying no innovation was adopted).

For risk-neutral farmers, the decision to adopt IFIs is based on comparing the expected utility of wealth from adoption $U_{jt}(\omega)$ against wealth from other alternative sets of multiple integrated farm innovations $U_{kt}(\omega)$, where (ω) represents the amount of wealth. Therefore, farmers will adopt a particular set of innovation only if $\tau_{jht} = \max(U_{jt}(\omega)$ - $U_{kt}(\omega) > 0.forj \neq k$, noting that the utility of adopting farm innovation is expressed as a function of farm, village and household variables. Following Mac-Fadden (1973), Khonje et al. (2018) and Kessie at al. (2018), the probability, that farmer household h at time t will adopt innovation j can be estimated using MNLM as follow:

$$\mathrm{Prob}_{ht}\left(\tau_{jht}< 1|X_{jht}\right) = \frac{\exp(\alpha_j + \mathrm{X}_{ht}\beta_j + \overline{\mathrm{X}}_{ht}\eta_j)}{\sum_{k=1}^{j}\exp\left(\alpha_k + \mathrm{X}_{ht}\beta_k + \overline{\mathrm{X}}_{ht}\eta_k\right)} \quad (1)$$

Where X_{jht} represent the matrix of observable farm, households and village attributes, $\overline{\mathrm{X}}_{ht}$ denotes time constant unobservable factors. According to Mundlak (1978) $\overline{\mathrm{X}}_{ht}$ is proxy by using the mean values of all time-varying covariates that are included in MNLM as additional variables. In the results and discussions, the section 5.1 contains the results from MNL model.

In the second stage, we estimate the Multinomial Endogenous Switching Regression (MESR) model to derive the relationship between welfare outcome variables (hybrid maize and pole beans yields; farm income, and equivalised food consumption per capita) and the set of regressors (Z) for IFI adopters and non-adopters for each farm innovation choice while keeping non-adoption $j = 0$ as the reference point. The welfare outcome equations for adopter and non-adopters of IFI choices can be expressed as follow:

$$\begin{cases} \mathrm{Regime1}: y_{0ht} = Z_{0ht}\beta_0 + \widehat{\lambda}_{0ht}\rho_0 + \overline{Z}_{0h}\alpha_0 + \mu_{0ht} if\, j = 0 \\ \vdots\vdots\vdots\vdots \\ \mathrm{RegimeJ}: y_{jht} = Z_{jht}\beta_j + \widehat{\lambda}_{jht}\rho_j + \overline{Z}_{jh}\alpha_j + \mu_{jht} ifj = J, 1, \ldots, 4 \end{cases} \quad (2)$$

Where y_{jht} are the outcome variables for farm household h, from the regime j at time t; Z is set of observable farm, village and household attributes; $\widehat{\lambda}$ represents the Inverse Mills Ratios (IMRs) calculated from equation (1), which is used to account for selection bias from time varying unobserved heterogeneity effects; ρ is the covariance between error terms from outcome and adoption equations; β_j and α_j are the parameters to be estimated; and μ_{jht} are assumed to be normally distributed with $E = (\mu_{jht}|X, Z) = 0$ and $Var = (\mu_{jht}|X, Z) = \sigma_j^2$.

Because of the choice model estimation process, we have also introduced the mean values of all time-varying variables ($\overline{Z}$) to parameterize the time invariant unobservable variables (Kessie et al, 2018). In estimating the MESR model, we bootstrapped equation (2) to control for possible heteroscedasticity that may arise from included controls variables due to the two-stage estimation technique.

It is important that, for the explanatory variables (X) in equation (1), MNLM must have at least one instrumental variable in addition to those created by nonlinearity of the selection equation from IFI adoption decision in equation (2) to be identified (Khonje et al., 2018; Di Falco et al., 2011; Kessie et al, 2015). In this study, to account for this exclusion restriction, we have used the following variables as instruments (IVs): Awareness of farm household on agricultural extension services and group/cooperative membership of the farm household. In Rwanda, normally, farm households can only buy improved seeds, fertilizers or pesticides from either public markets, farm cooperatives or village seeds providers. In addition, the information from agricultural extension service providers play crucial roles on farmers' decision to adopt IFI. Therefore, farmers will only adopt IFI if they know of the potential benefits (Adegbola & Gardbroek, 2007) or have past experience (Aldana et al., 2011). It is in this respect that we can claim that the intervention variables can affect the outcome variables only through adoption decisions (Khonje et al., 2018).

4.2. Conditional expectations and average treatment

Equation (2) is used to derive the expected actual values (equation (3) and the hypothetical values (Equation (4) to compare the expected outcomes from adopting IFI choices j. From Equation (2), we define the expected values of IFI adopters and non-adopters (hypothetical) as Equations (3) and (4).

$$\mathrm{E}(\mathrm{y}_{jht}|U = j, Z_{jht}, \overline{Z}_{jh}, \widehat{\lambda}_{jht}) = Z_{jht}\beta_j + \overline{Z}_{jh}\alpha_j + \widehat{\lambda}_{jht}\rho_j \quad (3)$$

$$\mathrm{E}(\mathrm{y}_{0ht}|U = j, Z_{jht}, \overline{Z}_{jh}, \widehat{\lambda}_{jht}) = Z_{jht}\beta_0 + \overline{Z}_{jh}\alpha_0 + \widehat{\lambda}_{jht}\rho_0 \quad (4)$$

. Following Khonje et al (2018), we estimate the Average Treatment on Treated (ATT) from adopting IFI choices by taking the difference between Equation (3) and Equation (4) as follows:

$$\mathrm{ATT} = \mathrm{E}(\mathrm{y}_{jht}|U = j, Z_{jht}, \overline{Z}_{jh}, \widehat{\lambda}_{jht}) - \mathrm{E}(\mathrm{y}_{1ht}|U = j, Z_{jht}, \overline{Z}_{jh}, \widehat{\lambda}_{jht}) = Z_{jht}(\beta_j - \beta_0) + \overline{Z}_{jh}(\alpha_j - \alpha_0) + \widehat{\lambda}_{jht}(\rho_j - \rho_0) \quad (5)$$

The first term of Equation (5) implies that expected change in mean values of the outcome variables for adopters and non-adopters are due to similar observed attributes. The second term indicates that expected changes in the mean outcome values are due to time-varying unobservable covariates differences. The last term in Equation (5) accounts for selection bias originating from time-invariant unobserved attributes.

5. Results and discussion

This section presents and discusses the main results of the study. First, it examines the probabilities of farm households' choice of agricultural innovations. Second, we derive the relationship between the welfare outcomes and decision of adopting farm innovations.

5.1. Drivers explaining the adoption of IFI

In the first stage, we derive the MNL model from adopting various single technologies (including hybrid maize, improved seeds of beans, fertilizers, pesticides, soil irrigated and drainage and terracing) and agricultural innovations of any random possible combination between soil, inputs and crop innovations. Table 2 shows the marginal effects estimates, where model 1 is for adopting single technology, model 2 is for adopting any two random combinations of the technologies, and model 3 is for adopting systematic farm integrations- three technologies. As shown in Table 2, the marginal effects are significantly different across farm innovation choices. The age of household head has a negative effect on adopting three technologies, which is similar to the results of Teklewold et al. (2013). Probably, this could be induced by the risk averse and mistrust characters (Verkaart et al., 2017; Bezu et a., 2014). The effect of household size shows an inverted U-shaped effect on technology adoption, but this effect is not statistically significant as found in Manda et al. (2016). Land has a U-shaped effect on adopting technologies, and this effect is statistically significant in all three cases. The U-shaped nature of the relationship implies that households with relatively larger farm plot sizes are more likely to adopt technologies. This could, first, be explained from the scale perspective since lumpy technologies require economies of scale to ensure profitability (Feder et al., 1985). Second, households with large farm sizes can allot a portion of their land for experimentation of new technologies (Uaiene et al., 2009). This could come as a serious constraint for those farmers who operate much smaller lands. On the contrary, the number of livestock does not significantly influence the decision to adopt modern agricultural technologies in all three models. Interestingly, farmers

Table 2
Marginal effects of integrating farm innovations using EICV panel data 2010 and 2014 rounds.

Variables	Model 1 Coeff.	Std.error	Model 2 Coeff.	Std.error	Model 3 Coeff.	Std.error
Age household head	−0.086	(0.056)	−0.087	(0.056)	−0.179	(0.054)***
Household size	1.526	(2.018)	1.642	(1.992)	1.455	(2.164)
Household size squared	−0.744	(0.971)	−0.799	(0.958)	0.679	(1.044)
Household land size	−0.540	(0.125)***	−0.542	(0.124)	−0.307	(0.126)**
Household land size squared	0.209	(0.078)***	0.207	(0.077)***	0.152	(0.074)**
Number of livestocks	−0.080	(0.172)	−0.064	(0.172)	−0.174	(0.175)
Number of livestocks squared	0.140	(0.314)	0.111	(0.313)	0.303	(0.319)
Education of household head	0.050	(0.031)	0.051	(0.031)*	0.000	(0.032)
Household got farm loan	0.273	(0.097)***	0.289	(0.098)***	−0.178	(8.064)
Farm household with cattle	−0.010	(0.043)	−0.014	(0.043)	−0.040	(0.042)
Household with non-farm business	0.048	(0.037)	0.047	(0.037)	0.030	(0.035)
Farm household has salary/wage	0.033	(0.037)	0.035	(0.037)	0.007	(0.035)
Farm household benefit VUP policy	−0.079	(0.036)**	−0.085	(0.036)**	−0.107	(0.037)***

The data are derived from EICV3-4 of sampled rural farmers. In model 1, we derive multinomial logit estimates of adoption of single agricultural innovation. In model 2, we estimated a multinomial logit estimates of adoption of multiple agricultural innovations of any possible combinations between soil, inputs or crop innovations. In the model three, we estimate multinomial logit estimates of integrating the following combinations: Crop and soil innovations, crop and input innovations and soil and input innovations, respectively. The standard errors in parenthesis. Non-adoption is the references in all estimations. ****P < 001, **P < 0.05, *P < 0.1.*

benefiting from the Vision Umurenge Program (VUP) reduced the probability of adopting multiple integrated farm technologies.

In Rwanda, the "Vision 2020 Umurenge" program is the government initiative in collaboration with development partners to leverage the resources by providing technical and financial assistance to poor households in the country, with the aim of accelerating the rate of poverty reduction in Rwanda (NISR, 2008). Usually, the VUP beneficiaries get either monthly financial support or employed by local administrative entities and paid. The negative effect could be linked to the fact that poor farm households could not use the meagre financial support they received to adopt farm investment technologies, but instead, they opt to use it for direct consumption.

Education shows a significant positive effect only in the case of model 2. The positive effects of education is consistent with several other studies, such as Asfaw et al. (2012), Bezu et al. (2014), Jaleta et al. (2016), and Manda et al. (2016). Education facilitates the understanding, processing and use of information. These critical factors influence the probability that a farmer adopt a new technology. Access to farm loans increases the probability that a farmer will adopt an improved farm technology. However, this result is only significant for single and any two random combinations of the technologies. In contrast, Tekle-wold et al. (2013) found the effect of credit to be negative in some instance of adopting integrated technologies. In rural areas of Rwanda, where only 4 percent of farm households have access to farm credit, improved access to credit can remove/minimize the liquidity constraints faced by farmers in adopting integrated technologies.

5.2. Cumulative distribution of yield and integration of technologies

Figs. 3 and 4 show the cumulative distribution of farm yields for maize and beans conditional on integrated agricultural technologies. In Fig. 3, it is clear that the CDF function shifts down from no adoption to single technology adoption. This implies that the yield of maize conditional on integrating a single technology is higher. The curve further shifts down, once we increase the bundle of technology integration. As shown in the figure, the CDF for three bundle of technologies shifts further down, suggesting that, albeit, integrating technologies can improve the yield of maize, the impact is greater when farmers apply increased bundle of technology integration.

Fig. 4 shows a similar trend for the yield of beans. Integrating technologies, whether single or a bundle of technologies shifts the CDF curve downwards, an indication of the fact that, the yield of beans improve significantly but more especially when bundle of farm technologies are adopted. In both cases, we tested the equality of the four alternative innovation choices using a Kolmogorov-Smirnov test, and the results showed a rejection of the equality at 5 percent.

5.3. Effects of IFI adoption on farm yield

Next, we computed the average treatment effect for different levels of technology integration on household welfare. Table 3 shows the results when we integrated single technologies. In the case of the yield of maize, adopting crop innovation, input innovations, and soil innovation improves the yield significantly. For crop innovation, maize yield increases by approximately 85 Kilograms per hectare between adopters and non-adopters. Adoption of input and soil innovations increase maize yield by 6 and 17 Kilograms per hectare between adopters and non-adopters, respectively. Although there seem to be differences between adopters and non-adopters of single technologies, these differences in nominal terms look relatively small. We can also see that adopting crop innovation (modern seeds) would yield to relatively higher maize produce than other type if innovations.

Regarding the beans farm yield from use of single innovations, we find that again crop innovations (mainly modern seeds) would make a significant difference between adopters and non-adopters with 271 Kg/ha more for adopters than non-adopters. Interestingly, we find that there is no difference between adopters and non-adopters on beans farm yield when input innovations. The results apparently indicate that except the use of crop innovation which make significant difference to a certain degree, the rest are somehow indifferent between adopters and non-adopters.

Looking at this evidence, it seems obvious that combining various farm innovations would improve farm yield than single innovations and the results reaffirm existing Mutenje et al. (2016) and Khonje et al. (2018).

However, as noted by Becerril & Abdulai (2010), adoption of technologies should involve bundles instead of single technologies. Table 4 shows the results when we integrated the different technologies. These integrations are defined into four categories as follow: $C_1I_1S_0$ is the combination of Crop and Input innovations; $C_1I_0S_1$ stands for the combination of Crop and Soil innovations; $C_0I_1S_1$ is for the Inputs and Soil combinations while $C_1I_1S_1$ represent the three elements all combined. In all specifications, we consider non-adopters as the baseline. It is clear from Table somebundles of technologies increase the yield of both maize and beans albeit small magnitude. Specifically, in both cases, integrating two technologies (crop and soil innovation) seem to provide the greatest benefits. Looking at the average treatment effect estimates, combining crop and soil innovations increases the yield of maize by 52 kg and the yield of beans by 127 Kg, respectively. The results indicate that improved seeds and soil mechanisation is best channel to increase farm

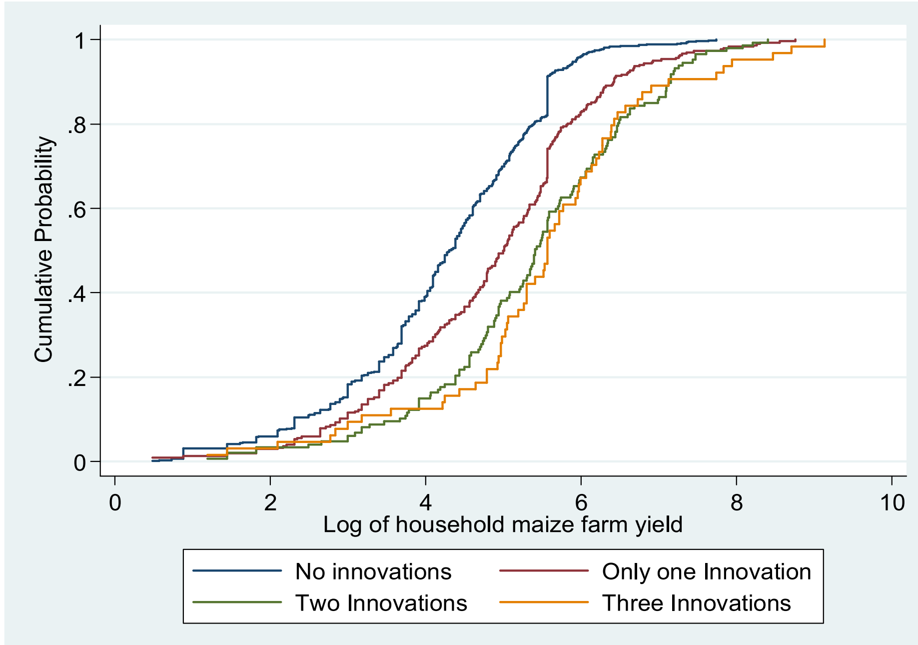

Fig. 3. Cumulative Distribution of Maize Yield across various IAI.

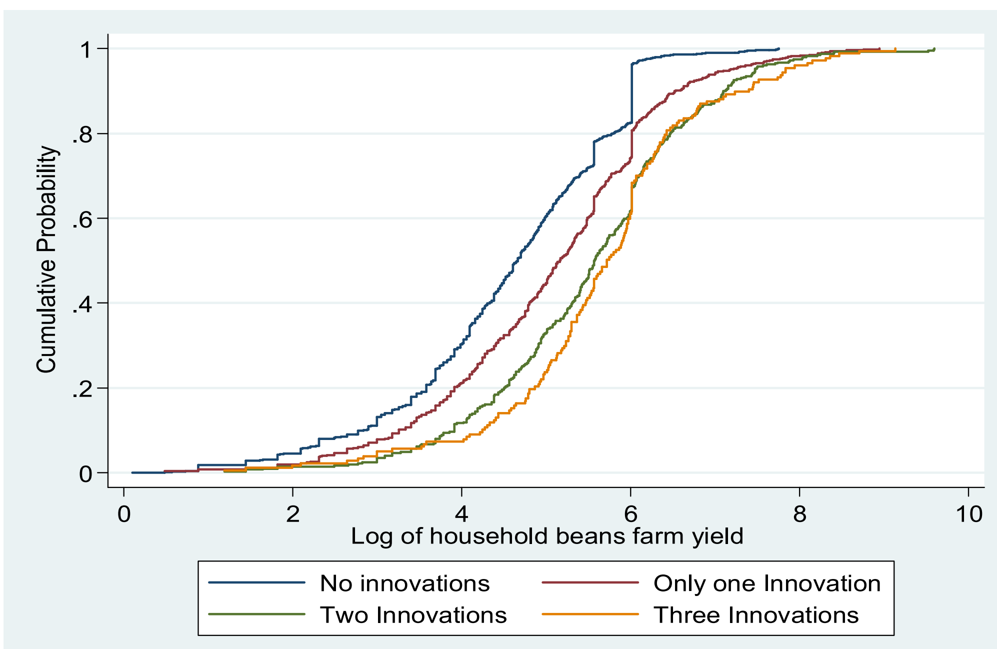

Fig. 4. Cumulative Distribution of Beans Yield across various IFI.

yield for the smallholders farmers. Surprisingly, the findings show that combining crop and input combinations does not provide statistical difference between adopters and non-adopters in farming beans. And so, this indicates that crop innovation such as improved seeds is a sine qua none for the smallholder farmers to increase productivity of both beans and maize which are the main stake of the Rwanda meals. Another string result from Table 4 indicates that combining all three innovations does not necessarily provide highest farm yield for smallholder farmers in Rwanda. Nevertheless. The the gains from innovation are likely to be higher for different bundles of technologies that single adoption. Kassie et al. (2015), Khonje et al. (2018) and Manda et al. (2018) all provide evidence that is consistent with the conclusion that adopting higher order packages of technologies/innovation provided greater productivity gains for maize farmers.

The following three important implications can be deduced from the result. First, the adoption of integrated technologies can impact positively on the food security level in Rwanda, as the two crops (maize and beans) play paramount role in food diet in the country. Second, assuming away market risks and potential post-harvest losses, the adoption of integrated technologies can enhance the incomes of farm households. Third, integrated farm innovations can also reduce the income inequalities in rural communities (especially if these interventions benefit poor households the more) and even close the inequality gap between the rural population and urban population. This could certainly

Table 3
Average Treatment effects (ATE) from MESR of single innovation on farmers welfare.

Choices of farm innovations	Adoption decision To adopt (*i = 2,3,4*)	Not to adopt (*i = 1*)	Average Treatment effects
	Mean value of hybrid Maize farm yield (Kg/ha)		
Crop innovations	351	266	85**
	(74.4)	(34.4)	(55.6)
Input innovations	121	115	6**
	(5.4)	(7.0)	(4.7)
Soil innovations	121	104	17***
	(5.6)	(5.9)	(3.9)
	Mean value of hybrid beans farm yield (Kg/ha)		
Crop innovation	505	234	271***
	(101)	(30)	(80.7)
Input innovations	132	126	5
	(7.7)	(7.3)	(6.3)
Soil innovations	179	133	46***
	(7.8)	(9.6)	(7.9)

Notes: MESR stands for Multinomial Endogenous Switching Regression. The table provides the effect of various single farm innovation adoption on farm household livelihoods. The standard errors in parenthesis. Non-adoption is the references in all estimations. ****P < 001, **P < 0.05, *P < 0.1.*

Table 4
Average Treatment effects (ATE) from MESR of IFI on smallholder farmers welfare.

Choices of farm innovations	IAI adoption decision To adopt (*i = 2,3,4, 5*)	Not adopt (*i = 1*)	Average Treatment effects
	Mean value of hybrid Maize farm yield (Kg/ha)		
$C_1I_1S_0$	171	126	45***
	(21.2)	(12.7)	(15.5)
$C_1I_0S_1$	186	134	52**
	(37.7)	(18.8)	(33.4)
$C_0I_1S_1$	142	97	45***
	(13.4)	(11.1)	(8.4)
$C_1I_1S_1$	112	98	14**
	(8.6)	(10)	(10.1)
	Mean value of hybrid beans farm yield (Kg/ha)		
$C_1I_1S_0$	147	146	1.00
	(15.6)	(13.4)	(12.1)
$C_1I_0S_1$	270	143	127***
	(47.9)	(28.6)	(53.7)
$C_0I_1S_1$	162	144	18**
	(13.7)	(14.9)	(14.8)
$C_1I_1S_1$	197	115	82***
	(17.1)	(8.4)	(14.3)

Notes: MESR stands for Multinomial Endogenous Switching Regression. The table provides the effect of various combination of farm innovation adoption and their implications on the livelihoods of smallholder farmers. The standard errors in parenthesis. Non-adoption is the references in all estimations. ****P < 001, **P < 0.05, *P < 0.1.*

yield some economic, social and political dividends in Rwanda.

5.4. Effects of farm innovations on farm income and food expenditure

While efforts can be made to minimize post-harvest and market risks, in reality, it may be difficult to eliminate these risks entirely especially in an economy like Rwanda where markets and infrastructure are yet well developed. In such situation, the perceived welfare gains obtained above using production outcome variables can be misleading. Therefore, in this section, the authors computed the average treatment effect of integrating technologies on total household farm income and food expenditure. Table 5 shows the results. Integrating a single technology increases household income by 43 percentage points. This increases to

Table 5
ATE from MESR Model of agricultural innovations on farm household welfare.

Choices of farm innovations	MAI adoption decision To adopt (*i = 1,2,3*)	Not to adopt (*i = 0*)	Average Treatment effects
	Mean value of farm income (Frws/hh)		
Only one innovation	230,043	160,409	69633***
	(20802)	(12338)	(15948)
Two innovations	267,868	177,743	90124*
	(8640)	(48698)	(48902)
Three innovations	667,873	235,738	432135*
	(462003)	(7359)	(462191)
	Mean value of food expenditure(Frws/hh)		
Only one innovation	199,019	154,159	44859***
	(4074)	(3515)	(3502)
Two innovations	215,198	196,350	18848***
	(4701)	(6880)	(6154)
Three innovations	200,533	179,677	2085***
	(9099)	(6374)	(7856)

Notes: MESR stands for Multinomial Endogenous Switching Regression. The table provides the effect of various combinations of agricultural innovations and their implications on household livelihoods. The standard errors in parenthesis. Non-adoption is the references in all estimations. ****P < 001, **P < 0.05, *P < 0.1.*

51 percentage points when two bundles of technologies are integrated. The gains further increase to 183 percentage points when a bundle involving three technologies are integrated. Clearly, these numbers suggest that integrating higher-order bundle of technologies generates greater incomes than lower-order bundle of technologies. In other words, had farmers not integrated technologies, they could have suffered an income loss of 8 percentage points (from one technology to two), 140 percentage points (from one technology to three), and 132 percentage points (from two innovations to three innovations). Khonje et al. (2018) and Manda et al. (2015) also found that integrating multiple technologies generates higher income for household farmers.

The story on the impact of adopting bundle technology on household food expenditure is different. The results confirm the fact that integrating technology enhances household food expenditure by 29 percentage points (in single technology case), 10 percentage points (in two technology case), and 1.16 percentage points (three technology case). The lower positive gains on food expenditure for integrating bundles of technologies could be interpreted to mean diversion of farm income resource to either savings, investment in child education and health, or build-up of household assets.

6. Conclusion and policy relevancy

In this study, we have employed a two-stage Multinomial Endogenous Switching Regression Model to examine the farmers' decisions to adopt multiple integrated technologies and how the adoption of these technologies affects the rural household welfare in Rwanda. The empirical findings provide several new insights into the adoption of various IFIs. Quite interesting was to find that smallholder farmers were intensively able to increase the adoption of IFIs between 2010 and 2014, the periods under which the sample panel datasets were collected. The results suggest that adopting multiple integrated farm innovations yield important increasing effects on smallholder farmers' welfare. Specifically, we find that IFIs induce positive and significant effects the crop yield (maize and beans), farmers' income and food expenditure. Notwithstanding, the dividends obtained in terms of higher yield, income and food expenditure are much more when farmers adopt suites of farm innovations in the agricultural sector instead of single technologies. Further, the findings show that adopting higher-order suites does not necessarily improve household food expenditure, albeit positive impacts are recorded. Possibly, this could imply diversion of additional gains obtained towards investing into household assets and/ or towards

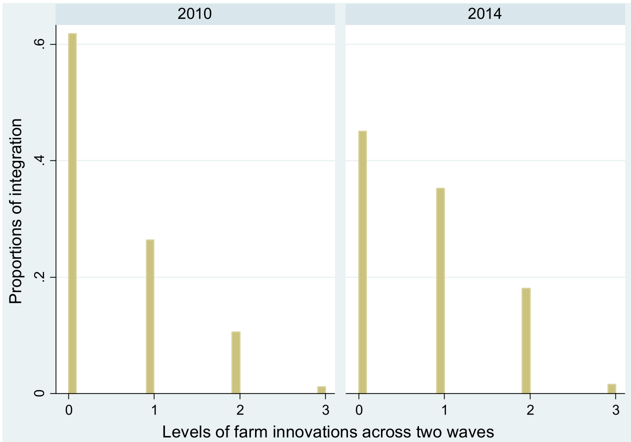

Fig. A1. Distribution of integrated farm innovations (IFI).

child education and health expenditure.

The study results have some policy implications. First, enhancing adoption of MIIs in the agricultural sector can be very beneficial in addressing country's economic hardships, such as poverty and food insecurity. The results suggesting a significant increase in farm productivity and income of the two crops (maize and beans) implying that the smallholder farmers can improve food access and food security. Further, assuming away market risks and potential post-harvest losses, the adoption of integrated technologies can enhance the incomes of farm households. Second, MIIs can also reduce the income inequalities in rural communities (especially if these interventions benefit poor households the more) and even close the inequality gap between the rural and urban citizens. This could certainly yield some economic, social and political dividends in Rwanda. Finally, the study provides suggestive evidence that access to credit and the education of the household head prove to be substantial in household decision to adopt MIIs. Consequently, efforts to improve access to and quality of education especially in rural communities can lead to sustainable and profitable farming. In addition, provision of soft loans targeting MIIs to smallholder farmers could equally yield great returns from farming. Therefore, given that the SSA countries, such as Rwanda, implement numerous policies that intended to transform the agricultural sector into a more competitive and market-oriented space, the results from this study can be useful. For instance, programs such as land use consolidation, and crop intensification programs have been designed to respond to the broader country's ambitions to increase farm productivity through high technology adoption and expanding the value addition of farm produce (Nsabimana et al., 2023). The positive and strong effect of the IFIs on productivity and limited effects on household food expenditure may elucidate how the policy makers in this space can adapt those policies accordingly and ensure that national targets to reduce poverty and food insecurity is effectively and timely achieved. In end, we would like to highlight the limitation of this study. First, the study relies of a smallholder panel dataset of ten years back. This may not necessarily represent the current Rwandan agricultural sector. Due to high variation between large and smallholder farmers, the study was conducted only using small scale farmers. Again, like the first data caveat, the results from this study can only be generalized to smallholder farmers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Table A1
Definition of farm and household attributes fused in this study.

Variables of interest	Definitions
Maize yield (Kg/ household)	The total annual maize farm yield from two farm seasons
Vegetables (Kg/household)	The total annual maize farm yield from two farm seasons
Farm income (Rwanda francs)	Annual farm income in given year
Food consumption pc(Rwanda francs)	Annual total household food expenditure (equivalized)
Input innovations (1/0)	Dummy, 1 if farmers use input innovation and 0 otherwise
Crop innovations (1/0)	Dummy, 1 if farmers use crop innovation and 0 otherwise
Soil innovations (1/0)	Dummy, 1 if farmers use soil innovation and 0 otherwise
Age of household head	Age of farm household head in each sampled household
Household size	Size of household members in each sampled household
Gender of household head (1/0)	Dummy, 1 if household head is male and 0 otherwise
Education of household head	Dummy, 1 if household head is educated and 0 otherwise
Salary/wave in household (1/0)	Dummy, 1 if household has salary/wage and 0 otherwise
Household is part of VUP (1/0)	Dummy, 1 if household benefit VUP and 0 otherwise
Awareness of agricultural policies	Dummy, 1 if household is aware of policies and 0 otherwise
Cooperative member (1/0)	Dummy, 1 if farmer is cooperative member and 0 otherwise
Household land size (ha)	The total land size of the farm household (hectares)
Have livestocks (1/0)	Dummy, 1 if farmer has livestock at home and 0 otherwise
Household has farm loan (1/0)	Dummy, 1 if farmers received farm loan and 0 otherwise
Number of cattle in household	The number of cattles in farm households
Non-farm business(1/0)	Dummy, 1 if farmer has non-farm business and 0 otherwise
Kigali (1/0)	Dummy, 1 if household is located in Kigali and 0 otherwise
Southern province	Dummy, 1 if household is located in South and 0 otherwise
Western province	Dummy, 1 if household is located in West and 0 otherwise
Northern province	Dummy, 1 if household is located in North and 0 otherwise
Eastern province	Dummy, 1 if household is located in East and 0 otherwise

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