Does Agricultural Extension Promote Technology Adoption? Empirical Evidence from Sri Lanka

B.R. Walisinghe*, S. Ratnasiri, N. Rohde and R. Guest

Griffith University, Australia

Abstract

This study explored the effect of extension contact and the individual technology adoption behaviour of farmers using probit models with an instrumental variable approach. Extension contact primarily involves delivering the technical know-how, instructions, and hands-on training springing from research. Results reveal that extension service is recognized as the driving motive for rice technology adoption, having the most significant effect over the other socio-economic factors. Therefore, emphasis on public extension service programs is noteworthy. Hence, further investment in agricultural research and development that allows extension services to continue may ultimately achieve sustainability of technological innovations leading to economic growth in developing economies.

Key words: adoption, extension service, rice technologies

Jel codes: C26, O33, Q16

1. Introduction

Adoption of technologies generated in the Research and Development (R&D) process is important for productivity growth (Griffith et al., 2004). Technology adoption has thus been discussed in studies analyzing the various facets. For example, Parente and Prescott (1994) in their seminal work explored which firms choose which technologies to adopt and the timing, within the context of a growth model. Furthermore, various authors such as Acemoglu et al. (2007), Bessen (2002), Easterly et al. (1994), Lahiri and Ratnasiri (2012, 2014), Nkonya et al. (1997), Sunding and Zilberman (2001), and Teklewold et al. (2013) have also analyzed the technology adoption behaviors of firms/individuals.

One strand of the above literature details technology adoption in the agricultural sector. In particular, studies like those of Laxmi and Mishra (2007), Mendola (2007), Saha and Chattopadhyay (2006), Sheikh et al. (2003), Villano et al. (2015) explain the technology adoption behavior of farmers. In this strand of literature, the discovery of agricultural technologies and their adoption have been identified as an engine of growth in agriculture (Eklund, 1983; Sunding & Zilberman, 2001; Thornton, 1973). With rapid population growth and demand for more food, the need for the adoption of novel technologies in agriculture has been emphasized (Cole, 1999; Devi et al., 2014; Diiro & Sam, 2015). In the context of agricultural technology adoption, extension services play a key role in the diffusion of technological innovations.

Extension services defined

Extension services primarily involve delivering the technical know-how, instructions, and hands-on training springing from research. Extension services in fact are identified as a key mode of technology transfer (Birkhaeuser et al., 1991; Dalton, 1980; Tripp et al., 2005). The technologies discovered at research level have to be disseminated to the prospective users for effective adoption (Cole, 1999; Shah et al., 2014). The dissemination role is played mainly by the extension services in the agricultural sector. In Sri Lanka, the extension service is provided free of charge mainly by the public institutions, to promote novel technologies generated at research centers to improve the productive efficiency of farms[1].

In the context of technology adoption behavior of farmers in response to extension contact, Hussain et al. (1994) were the first to explore the direct relationship between the practice and its impact on the technology adoption behavior of farmers. They examined the impact of the Training and Visit (T&V) system on the adoption of improved wheat technology, and stated that T&V had improved the farmers' knowledge and adoption of the technology. Moreover, Sheikh et al. (2003) have highlighted that the number of extension visits has a significant influence on the adoption of 'no-tillage' technologies by farmers in Pakistan's Punjab.

In addition, there are a few studies in extant literature that explore the impact of extension service on technology adoption; however, these studies analyze the implications indirectly. For example, using cost and benefit estimations, Feder and Slade (1986) have explored the effect of the Training and Visit (T&V) extension system on farmers' knowledge in the Hariyana state of India, and have found that the T&V system had led to rapid diffusion of knowledge in the area, leading to productivity improvement in the wheat-paddy cropping system. A similar study by Tripp et al. (2005) has examined the effect of Farmer Field

[1] Extension service is also provided by the private sector as an advertising strategy for product promotion

School (FFS), a form of extension service, which has been introduced to Sri Lankan rice farmers to disseminate principles of Integrated Pest Management (IPM). The implications have been that, although the studies on FFS have influenced the reduction of insecticide use, they did not have the capacity to derive explicit conclusions of the effect of FFS.

In this study, therefore, we focus on this unexplored relationship: extension service and technology adoption. More precisely, the objective of this study is to assess the effect of extension service on the technology adoption behavior of rice farmers. Our study helps to draw implications in relation to the cost effectiveness of the government spending on extension programs which have aimed at wider diffusion and adoption of technologies by farmers (Feder et al., 2004; Nkonya et al., 1997). We use data from the Department of Agriculture, Sri Lanka to explore the effect of extension service on rice technology adoption in a rural farming context.

The novelty of our study is two-fold. Firstly, we add a unique and solid finding to the literature on technology adoption behavior by exploring the *direct link* between receipt of agricultural extension services and farmers' technology adoption behavior. Many studies have treated the extension service variable as an indirect input and have more focused on productivity improvement as the ultimate objective. We attempted to isolate the effect of extension service provided by the public sector, as this is a public good provided free of charge in Sri Lanka, and we explored the implications for farmers' adoption behavior. Finally, we aimed to contribute to the literature by reiterating the significance of extension and training service as a direct motive for the technology adoption behavior of farmers.

Secondly, this study highlights the essential use of instruments in empirical estimations when endogeneity bias is present. The technology adoption decision was regressed with potential regressors and we adopted an instrumental variable (IV) approach to avoid potential endogeneity bias often found in cross sectional studies. In this study the extension service variable was identified as endogeneous and instrumented in the technology adoption context.

Organization of the paper is as follows. The next section provides a brief overview of the Sri Lankan rice sector. Analytical methods used are discussed in Methodology and the findings are summarized in Results and Discussion. Conclusions and implications derived from the study are outlined at the end.

2. Case of Sri Lanka

We choose Sri Lanka as a case study to analyze our hypotheses; that is the public extension services may promote technology adoption in the farming context. We focus on the rice sector in the island, and provide a synopsis of technology adoption of rice sector in Sri Lanka below.

The country has achieved self-sufficiency in rice owing to adoption of improved rice technologies and public investment on R&D in the rice sector. Rice farming has been identified as a major development strategy and a coping mechanism in uplifting the livelihood of rural households in Sri Lanka. Rice occupies nearly 12% of arable land in the country and more than 1.8 million farm families rely on rice culture as their major income source (Socio Economics & Planning Centre, 2013). Rice is grown in two major seasons: *Maha* (wet season) and *Yala* (dry season), respectively coinciding with the northeast and southwest inter-monsoonal rains (Dhanapala, 2000). In 2014, the rice production in Sri Lanka was 3.38 million metric tons, which had declined by 27% compared to 2013, due to adverse drought spells. The average yield was 4.2 metric tons per hectare and the per capita rice consumption reached 110 kg/head/year by 2014 (Central Bank of Sri Lanka, 2014) .

Commencing with the green revolution, rice technology generation and its adoption have paved the way to achieve self-sufficiency in rice and to escape from heavy import dependence (Hossain et al., 2006). The Rice Research and Development Institute (RRDI) is the state owned agency responsible for the generation of rice production technologies, and primary dissemination of same in Sri Lanka. Since 1952, RRDI has released approximately 75 rice varieties and has identified several promising associated technologies. Rice technologies are released to the farmers after a recommendation by the technology release committee.

There are various technologies available for rice production in Sri Lanka. The leading technology is the development of new varieties. According to the Rice Research and Development Institute (2013), approximately, 99% of the total rice area has been cultivated by New Improved Varieties (NIV). In addition to rice varieties, a limited spread of associated technologies can be seen among the farming communities. For instance, the percentage of adopting the Parachute method (seedling broadcasting) was 0.6% and the organic fertilizer use was 3.17% of the area under rice in 2013 (Department of Census & Statistics, 2014).

The technology generation process is followed by a sequential dissemination effort by "extension agents". Most of the technologies generated at research level in Sri Lanka are delivered to farmers via extension programs. The leading extension service provider in the country for rice producers is the public sector. This service is provided free of charge to the farmers and administered by the state Agrarian Services Department.

3. Methodology

In this section, firstly, we present an introduction to selected rice technologies, and a theoretical explanation of the individual's adoption behavior. Then we detail the empirical model estimation specified in the study.

3.1 Rice technologies

We primarily considered two groups of technologies. Rice varieties were treated as the first group, and the associated technologies were grouped into the second. A detailed description of the selected rice technologies is given below.

The study identified the rice varieties as one semantic group. Rice varieties have adaptability to varying agro-ecological conditions. The suitability to different environmental conditions has been tested at different locations before the release of a specific variety. Studies have identified that with the introduction of new improved rice varieties, the adoption of traditional and old improved varieties have shown a declining trend (Rice Research & Development Institute, 2013).

The second group in fact can be divided into two as areas of agronomic practices and establishment methods. Of the agronomic practices, three technologies were selected: organic fertilizer, Leaf Color Chart (LCC), and weeder. Organic fertilizer method is the application of organic materials such as rice straw, manure and leafy materials in the form of compost, instead of applying inorganic fertilizer. A LCC is a simple calibrator used to adopt need-based nitrogen fertilizer application to the rice plant according to the color codes and the N fertilizer use efficiency is enhanced from the technology (Silva et al., 1998). A Weeder is a hand operated machine used to control the weeds in rice cultivation, when rice is planted in rows, as inter-row tillage will enhance the available water and nitrogen in soil (Ascard & Mattsson, 1994).

Of the rice crop establishment technologies, zero tillage, Parachute method (seedling broadcasting), water seeding, and seeder were considered. In zero tillage, soil is not tilled or disturbed and initial land preparation by farm implements is avoided. This leads to reduced cost of cultivation and water saving (Erenstein & Laxmi, 2008). In the Parachute method, 14-day old rice seedlings are distributed instead of conventional seed broadcasting, the method labor saving for efficient cultivation (Zhang et al., 2008). In water seeding, the sprouted seeds are distributed on the puddled paddy terraces. South Asian countries including Sri Lanka, use water seeding as an alternate method for direct seeding. They broadcast seeds into flooded paddy fields to avoid extensive use of water and to control weed growth in paddy (De Datta, 1986). The seeder can be a hand operated or machine mounted drum/vessel used for row seeding (Togashi et al., 2001). This method is an alternative for row planting, and enables weed control and improved soil aeration of rice plant.

3.2 Empirical model estimation

The studies have shown that on many occasions, individual choices related to adopting a certain technology are made from a limited number of possibilities (Adesina & Zinnah, 1993; Hausman & Wise, 1978). For example, studies that explore adoption behavior often used a more simplistic discrete approach by identifying individuals either as "adopters" or "non-adopters" (Villano et al., 2015). In other words, these studies have used a binary model to measure the technology adoption. For this reason we use a probit approach to empirically test our hypothesis.

The type of individual choices discussed above that yields binary decisions is used in our analysis of technology adoption. The dependent variable is a binary that can have only two possible outcomes: either 1 or 0 representing adoption or non-adoption.

Thus we estimated the relationship using both logit and probit models, both yield a similar results (Maddala, 1986). Note that we report only the results of the simple probit estimation method.[2] We assumed that the model takes the following form that has a vector of regressors X.

$$\Pr(Y_i = 1) = \phi(X_i \beta_i) + u_i \tag{1}$$

Where, Pr denotes the probability of technology adoption, $\phi(.)$ is standard normal Cumulative Distribution Function, X_i is a vector of regressors with $n \times k$ matrices, β_i is $k \times 1$ vector of unknown parameters to be estimated, u_i is $n \times 1$ residual error, and unknown β_i parameters are estimated via Maximum Likelihood.

In the Ordinary Least Square (OLS) estimation, the assumption is that the expected value of the error term u_i, given the values of the regressors, is zero [$E(u_i | X_i) = 0$]. The resulting regression will produce consistent estimates. However, the problem of endogeneity within OLS occurs mainly due to one or more regressors that are correlated with the error term [$E(u_i | X_i) \neq 0$]. On many occasions, this problem arises due to (i) measurement error, or (ii) reverse causation with the dependent variable (simultaneity), or iii) an omitted variable in the regression (Angrist, 2001; Bhattacharya et al., 2006; Freedman & Sekhon, 2010). When endogeneity is present, the OLS produces biased and inconsistent estimates. Inclusion of an "instrument" (Z) in the regression produces consistent and unbiased estimates, and an ideal instrument should possess certain properties (Gujarati, 2015; Mullahy, 1997).

In order to be a good intrument, Z must satisfy three conditions: i) Z must be correlated with the stochastic variable [$\text{cov}(X_i, Z_i) \neq 0$]; ii) Z should not correlate with the error term [$\text{cov}(Z_i, u_i) = 0$]; and iii) Z should not belong to the original regression model as a regressor. The variance (ρ^2_{XZ}) of the instrument (Z) is larger than that of the variance of the OLS estimator. Hence the IV estimator is less efficient than the conventional OLS estimator. The variance of the instrument being close to one suggests that Z is a strong instrument, whereas it is close to zero, Z becomes a weak instrument (Gujarati, 2015; Mullahy, 1997).

The estimation of parameters in the instrumental variable (IV) approach involves two stages. This is known as "two-stage least squares" (2SLS), meaning that OLS is performed twice

[2] As the results are quite similar we avoid reporting them.

(Amemiya, 1974; Breusch et al., 1989). In the first stage, the suspected endogeneous stochastic variable is regressed on all the chosen instruments with the other regressors in the original model to derive estimates of the endogeneous regressor. In the second stage, the original regression is performed replacing the endogenous regressor by its estimated value from the stage 1 regression. Ensuring valid instruments in the regression is the most important aspect in the IV approach (Gujarati, 2015).

The Hausman specification test developed by Durbin, Wu and Hausman is used to test the validity of instruments (Hausman, 1978). The test evaluates the difference between the OLS estimators and IV estimators. If the difference is equal to zero, we do not reject the null hypothesis that the OLS and IV estimators are statistically the same and estimators are consistent (Gujarati, 2015). Hence the instruments confirm the validity in IV estimation, when regressors suffer from endogeneous bias.

In this study, when technology adoption behavior is regressed, the extension variable was identified as potentially endogenous, and the average extension by geographical area was used as the instrument in the regression. Extension service programs are quasi-randomly assigned across Sri Lankan regions and the propensity to adopt a technology is a choice for the farmers. Hence the regional averages make suitable instruments. Therefore, we instrumented the extension service variable in the probit model replacing the "average extension contacts" across regions to correct the endogeneity biases in our estimates.

We then modeled the technology adoption behavior as a function of extension service and included several socio-economic variables as control variables. The model is in the following form.

$$\Pr(Y_i = 1) = f(Ext_i, Ag_i, Ma_i, Edu_i, Occ_i, Inv_i, Fs_i, Inc_i, Own_i, Irr_i) \qquad (2)$$

Where, $\Pr(Y_i)$ is the probability of technology adoption by i^{th} farmer with a binary outcome; the explanatory variables are as follows (Table 1).

Choice of regressors is based on the literature, and past studies have proven them to have a significant impact on technology adoption. For instance, Eklund (1983), Heisey and Mwangi (1996), Kalirajan (1984), Koundouri et al. (2006), Namara et al. (2003), and Rauniyar and Goode (1992) have used extension contact in their adoption research. Ryan and Gross (1943) have shown that the adoption decision largely varies from farmer to farmer. Hence many socio-economic factors have been found to have an impact on adoption of new practices, and of these factors, operator/farmer specific characteristics, such as age of farmer (Koundouri et al., 2006; Namara et al., 2003; Norris & Batie, 1987), level of education (Daberkow & McBride, 2003; Feder & Umali, 1993; Kebede et al., 1990; Koundouri et al., 2006; Mottaleb et al., 2015; Namara et al., 2003; Norris & Batie, 1987), farming experience (Kebede et al., 1990), occupation (Norris & Batie, 1987), income status (Feder et al., 1985; Namara et al., 2003; Norris & Batie, 1987) and family size (Mottaleb et al., 2015; Namara et al., 2003) have been confirmed as having the greater impact. In addition to farmer specific characteristics, farmer managed conditions such as type of tenure (Daberkow & McBride, 2003; Eklund, 1983; Feder et al., 1985; Mottaleb et al., 2015; Namara et al., 2003) and irrigation supply (Koundouri et al., 2006; Mottaleb et al., 2015) of the farm land have also been combined with the adoption decisions. Accordingly, we have selected the following variables as regressors in the probit model.

Table 1. Explanatory variables of the regression

Variable Name	Description
Ext_i	Extension service received by farmer, measured in binary variable: 1 if received; 0 otherwise
Ag_i	Age of the farmer, measured in years
Ma_i	Gender of the farmer, measured in a binary variable: 1 if male; 0 otherwise
Edu_i	Education level of the farmer, measured in a categorical variable: lowest level is 1, if the farmer had primary education; highest is 5, if the farmer had tertiary education
Occ_i	Occupation of the farmer, measured in categorical variable: lowest is 1, if the respondent is a farmer; highest is 5, if government employed
Inv_i	Level of involvement of the farmer, measured in a binary variable: 1 if full time; 0 otherwise
Fs_i	Number of family members, measured in counts
Inc_i	Average monthly income of the household, measured in a categorical variable: lowest is 1, if income is < 10,000; highest is 5, if income is > 50,000
Own_i	Ownership of the land, measured in categorical variable: lowest is 1, if owned; highest is 3, if pawned
Irr_i	Irrigation mode, measured in a categorical variable: lowest is 1, if minor irrigation; highest is 3, if rain-fed

The relationship given in Eq. (2) was estimated for eight different technologies using a probit model. Then we calculated the difference in the probability of adopting technology, with and without extension service. For this purpose, we evaluated Eq. (2) at the means of the other explanatory variables for two situations: (i) $Ext_i = 1$; (ii) $Ext_i = 0$. Then we calculated the resulting difference between $\Pr(Y_i)$ to isolate the probability of a farmer adopting the particular technology when an extension service is present.

Coefficients of the binary choice models cannot be interpreted directly as they imply a latent probability of technology adoption. As in usual practice, marginal effects were computed to interpret the effects of changes in explanatory discrete variables (Verbeek, 2012). More precisely, when the explanatory variable was a dummy, as in the case of the extension service in our model, the effect of the extension service was estimated using marginal effects computed at the average of all the other explanatory variables. This was calculated for two scenarios: with and without the extension service. The resulting difference in the dependent variable explains the probability of adopting a certain technology, when the extension service is present.

3.3 Data

The study used a database of a cross sectional survey conducted by the Department of Agriculture, Sri Lanka in 2012 at *Ampara*, *Mannar*, *Polonnaruwa*, *Kurunegala*, *Gampaha,* and *Kegalle*, representing major rice producing districts in Sri Lanka operated under irrigated and rainfed conditions. The study sites represent three agro-climatic zones in the country; Dry (*Ampara, Mannar, Polonnaruwa),* Intermediate (*Kurunegala*), and Wet zones (*Gampaha, Kegalle*). Rice farming was the primary income source of 76% of farmers in the sample; those cultivating under irrigated condition was 80%, while rain-fed farmers were 20%. Of the total, 80% were full-time farmers and 72% were male respondents.

Table 2 presents the technologies considered and their options evaluated in the study. The awareness percentage of the rice technologies given in column 2 denotes the percentage of farmers who had awareness of each technology. The percentage of farmers' preference to adopt a given technology is given in column 3 while the percentage of farmers that were trained to use a given technology is given in column 4. The column 5 describes the percentage of farmers who adopted a given technology. Accordingly, 67% of farmers had prior knowledge on improved rice varieties. Even though 64% of farmers preferred to adopt the technology, only 35% have received training. Therefore, the adoption rate of improved rice varieties was only 60%.

Table 2. Rice technologies and levels of awareness, preference and adoption

Technology	Awareness (%)	Preference for Adoption (%)	Training received (%)	Adoption rate (%)
Improved rice variety	67	64	35	60
Organic fertilizer use	73	57	47	54
Seedling broadcasting (parachute)	72	52	45	30
Water seeding	35	28	30	21
Weeder	43	27	19	17
Seeder	40	27	18	11
Zero tillage	25	21	10	10
Leaf Color Charts	15	24	11	6

4. Results and Discussion

Table 3 illustrates the results of the probit model in respect of the selected rice technology adoption. All the regression coefficients of extension service variable (Ext_i) were indicative of a high level of significance in the probability of technology adoption. Therefore, we can infer that, when all the technologies were considered, the extension service programs were positively and significantly correlated with technology adoption.

The results further reveal that the probability of adopting rice varieties for those who received the extension service was 91%, while the probability was 23% for the farmers who had not received the trainings via an extension service. The difference between the two scenarios showed that the farmers receiving an extension service were 68.5% more likely to adopt the technology, compared to those who did not receive an extension service.

The results of the probit model with the instrumental variable approach are presented in Table 4, and the results are similar to the results in Table 3. However, the impact seemed to be much stronger. In all the technologies, the extension service variable was strongly and positively correlated with the probability of technology adoption. For instance, the probability of adopting rice varieties for the farmers who received an extension service was 96%, while it was 12% for those who did not receive an extension service. The results implied that, extension service has increased the probability of rice variety adoption by 84.37%, and the effects were more influential than the results without instrumentation. Compared to the other technologies, extension and training programs have been very effective in promoting the adoption of rice varieties, weeder, water seeding, and zero tillage technologies as the probability of adopting these technologies has increased by more than 80%.

In addition to the extension service variable, other socio economic variables such as age, education, occupation, level of involvement and income were indicated to have a significant effect on technology adoption. When the farmer was a full-time farmer, the adoption of zero tillage and of seeder was increased. Income had a positive effect on the use of Leaf Color Charts, as it needed some investment at the initial stage of practice. Gender and education also significantly influenced adoption, implying that male farmers are more likely to adopt, and the probability of adoption increased with education.

Table 3. Regression coefficients of *probit* model without instrumentation (Dependent variable: probability of adopting a technology)

Variable	**Rice Variety**	**Organic Fertilizer**	**Leaf Colour Chart**	**Weeder**	**Parachute**	**Water seeding**	**Zero Tillage**	**Seeder**
Ext_i	2.097***	1.746***	2.589***	2.094***	1.585***	1.922***	1.971***	1.837***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ag_i	-0.006	-0.003	-0.007	0.029***	-0.014*	-0.004	-0.006	0.011
	(0.311)	(0.525)	(0.608)	(0.000)	(0.015)	(0.518)	(0.412)	(0.136)
Ma_i	0.236	0.407	1.038	0.522	0.661**	0.039	-0.262	0.496
	(0.351)	(0.073)	(0.173)	(0.154)	(0.009)	(0.882)	(0.356)	(0.174)
Edu_i	0.049	0.213**	-0.033	0.155	0.123	0.008	-0.028	0.081
	(0.504)	(0.003)	(0.810)	(0.085)	(0.076)	(0.923)	(0.780)	(0.377)
Occ_i	-0.197*	-0.048	0.087	-0.040	0.011	-0.137	0.245*	0.080
	(0.046)	(0.547)	(0.741)	(0.722)	(0.890)	(0.238)	(0.039)	(0.536)
Inv_i	0.016	0.393	0.774	0.092	0.182	0.056	0.993**	0.648*
	(0.942)	(0.067)	(0.141)	(0.720)	(0.388)	(0.823)	(0.006)	(0.046)
Fs_i	0.023	0.020	-0.062	-0.607	-0.109*	0.042	0.087	-0.012
	(0.685)	(0.689)	(0.600)	(0.358)	(0.047)	(0.470)	(0.206)	(0.857)
Inc_i	-0.022	-0.078	0.424**	0.010	-0.027	-0.075	-0.022	-0.022
	(0.814)	(0.368)	(0.006)	(0.920)	(0.753)	(0.444)	(0.836)	(0.833)
Own_i	-0.079	0.085	-0.071	0.247	0.249*	0.073	-0.036	0.032
	(0.540)	(0.495)	(0.794)	(0.110)	(0.038)	(0.619)	(0.834)	(0.840)
Irr_i	-0.580***	-0.016	-0.366	-0.133	0.177	-0.345*	-0.102	-0.222
	(0.000)	(0.900)	(0.305)	(0.430)	(0.184)	(0.026)	(0.565)	(0.210)
Const	0.891	-1.555*	-3.517*	-3.682***	-1.739**	-0.277	-2.156*	-3.087**
	(0.177)	(0.016)	(0.021)	(0.000)	(0.006)	(0.706)	(0.014)	(0.001)
$LR\ Chi^2$ (10)	259.94	202.99	120.13	156.14	158.46	136.49	90.98	131.66
$PseudoR^2$	0.413	0.319	0.569	0.375	0.272	0.299	0.286	0.358
$\Pr ob > Chi^2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	457	461	421	445	458	433	419	448
[a]Probability; Extension=1	0.91	0.86	0.45	0.72	0.62	0.76	0.60	0.52
Probability; Extension=0	0.23	0.25	0.00	0.06	0.10	0.11	0.06	0.04
Difference (%)	68.58	60.69	44.99	65.72	52.41	65.55	54.20	48.72

* p<.05; ** p<.01; ***p<.001; [a] probability of technology adoption with and without extension service evaluated at the means of explanatory variables; p values in parentheses

Table 4. Regression coefficients of probit model with instrumentation (Dependent variable: probability of adopting a technology)

Variable	Rice Variety	Organic Fertilizer	Leaf Colour Chart	Weeder	Parachute	Water seeding	Zero Tillage	Seeder
Ext_i	2.942***	1.372**	2.788**	3.491***	1.990***	3.476***	3.443***	2.749***
	(0.000)	(0.001)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ag_i	-0.003	-0.003	-0.002	0.016*	-0.013*	0.001	-0.006	0.008
	(0.516)	(0.642)	(0.885)	(0.020)	(0.018)	(0.839)	(0.337)	(0.315)
Ma_i	-0.104	0.332	-0.291	0.296	0.551*	0.378	-0.026	0.460
	(0.628)	(0.138)	(0.578)	(0.231)	(0.020)	(0.070)	(0.2920)	(0.166)
Edu_i	0.057	0.223**	-0.022	0.021	0.104	0.063	-0.039	0.050
	(0.371)	(0.002)	(0.875)	(0.766)	(0.151)	(0.338)	(0.634)	(0.588)
Occ_i	-0.058	-0.064	0.111	0.008	0.052	0.007	0.255*	0.111
	(0.536)	(0.423)	(0.669)	(0.916)	(0.524)	(0.934)	(0.011)	(0.356)
Inv_i	0.003	0.397	0.680	0.186	0.249	0.056	0.843*	0.640*
	(0.985)	(0.058)	(0.198)	(0.294)	(0.217)	(0.770)	(0.010)	(0.033)
Fs_i	-0.006	0.022	-0.019	-0.048	-0.102	0.034	0.081	0.009
	(0.900)	(0.672)	(0.872)	(0.315)	(0.059)	(0.465)	(0.163)	(0.899)
Inc_i	-0.120	-0.056	0.403*	-0.093	-0.039	-0.109	-0.104	-0.094
	(0.148)	(0.550)	(0.011)	(0.225)	(0.651)	(0.154)	(0.262)	(0.370)
Own_i	-0.065	0.080	-0.036	0.077	0.241*	0.093	-0.045	0.011
	(0.558)	(0.520)	(0.897)	(0.514)	(0.046)	(0.412)	(0.746)	(0.942)
Irr_i	-0.362*	-0.099	-0.422	0.205	0.266	0.038	-0.026	-0.104
	(0.020)	(0.524)	(0.247)	(0.106)	(0.068)	(0.796)	(0.866)	(0.565)
Const	0.188	-0.421	-1.231	-2.383***	-1.609*	-1.738**	-0.379	-1.834*
	(0.751)	(0.542)	(0.356)	(0.000)	(0.013)	(0.002)	(0.558)	(0.018)
Chi^2	517.900	45.740	22.980	624.700	74.600	585.700	177.600	96.720
$Porb > Chi^2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	457	461	421	445	458	433	419	448
[b]Probability; Extension=1	0.96	0.81	0.53	0.99	0.71	0.99	0.98	0.81
Probability; Extension= 0	0.12	0.31	0.00	0.10	0.08	0.14	0.08	0.03
Difference (%)	84.37	50.04	52.95	88.41	63.51	85.51	89.85	78.01

* p<.05; ** p<.01; ***p<.001; [b] probability of technology adoption with and without extension service evaluated at the means of explanatory variables; p values in parentheses

Among the ten demographic variables considered, the extension service variable was the most significant factor that influenced adoption. Hence the results have proven that the extension service has a significant and positive influence in promoting the adoption of technologies and disseminating the technical know-how, leading to effective diffusion of innovations of rice technologies.

5. Conclusion

The study sought to explore the effect of extension services and the determining factors of rice technology adoption in Sri Lanka, within a limited dependent variable context. When individual technologies were considered separately, our results suggested that receipt of extension services has been the most significant factor for farmers to adopt rice technologies. Hence the extension service is recognized as the driving motive for rice technology adoption having the most significant effect on the other socio-economic factors. The implications suggest that, the investment on research and development targeting extension infrastructure enhances the probability of adopting the technologies, enabling diffusion of innovations. Therefore, the government emphasis on extension service programs will be beneficial for promoting technology adoption in the country. Hence, further investment in agricultural research and development that allows extension services to continue may ultimately achieve sustainability of technological innovations that lead to economic growth.

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