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Research paper

Application of Ordinal Logistic Regression Analysis in Determining Factors Affecting SIMLESA Technologies Adoption in Southern Ethiopia

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The study attempts to develop an ordinal logistic regression (OLR) model to identify the determinants of SIMLESA technologies using the data of 150 respondents interviewed during adoption monitoring Survey 2014 in southern Ethiopia. Based on the adoption index (score) the adopters are categorized into three groups-high adopter, partial adopter and low adopter. Since adoption status is ordinal, an OLR model employed to identify factors affecting technology adoption. The proportional odds model (PPOM) has also been developed to check the applicability of the OLR model. Based on the analysis result of this study, we find that Age, Education level & source of information were the significant predictors of technology adoption in the study area. However, our analysis also highlights that land size and total livestock unit were less significant to adopt the given technology. The study also revealed that the proportional odds assumption holds true. The findings clearly justify that OLR models is appropriate to find predictors of technology adoption. Therefore, the study suggested that more emphasis should be given for higher education and proper mechanism of information delivery system platform should be designed for the enhancement of technology adoption in the study area.

Keywords: Ordinal logistic regression model, Proportional odds model, SIMLESA,

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INTRODUCTION

Sub-Saharan Africa (SSA) is categorized as an agrarian economy where 32% and 65% of the region's total gross domestic product (GDP) and total labor respectively depends on (World Bank, 2007; Bach & Per, 2008). Sub-Saharan Africa region in general is known for its abject poverty, low level of agricultural productivity, low level of social and economic development, and lack of adequate infrastructure that promote overall change in development. The majority of the region`s population, 62.6%, live in rural areas. Of these, more than 70% of the poor depend on agriculture as their sole means of livelihood (IFAD, 2012).

The region's agricultural production depends on diverse agro-ecological and farming systems where farmers grow a wide range of crops and keep different types of livestock for their livelihood strategies. SSA is highly challenged in terms of poverty and hunger as well as ensuring environmental sustainability (Reynolds et al., 2007; Rockstrom et al., 2007).

The major challenges the agricultural sector in SSA faces include high population growth (which results in livelihood resources competition), increasing climate

Variability is declining levels of agricultural productivity, natural resource degradation and food insecurity (Biggs et al., 2004; Beintema & Stads, 2006). In order to enhance the agricultural productivity of the region, a special attention needs to be given to the smallholder1 farmers. Most of SSA smallholder farmers use small-scale rain-fed agricultural system categorizing them as; "the poorest, least educated, poorly linked to markets, most vulnerable to non-conducive policies and surrender more severely to unfavorable environmental conditions such as draught" (World Bank, 2007).

And more specifically, being in Sub-Saharan African region, Ethiopia's economy is predominantly an agricultural economy. Agricultural growth provides important basis for general economic growth as well as employment creation in the country. The agricultural Gross Domestic Product (GDP) of Ethiopia is 41 percent, export is 90 percent, employment is 85 percent and food security is high (World Factbook, 2012). The small-scale farming dominates the agricultural sector and accounts for 95 percent of the total area under crop and more than 90 percent of crop output. The livelihoods of 84% of the citizens depend on various agricultural productions (Fikremarkos, 2012).

Although agriculture is one of Ethiopia's most promising resources, the sector has been slowed down by periodic drought, high levels of taxation and poor infrastructure that often make it hard and expensive to get goods to market. Also, overgrazing, deforestation and high population density has led to massive soil degradation leading to low productivity. The above problems have made it hard for the country to feed itself—best. Since then, the country has experienced similar occurrences that expose a sizeable population to humanitarian needs. As things stand, over 3 million Ethiopians need food and other humanitarian assistance annually (SIDA, 2015).

Hence, it is the very essential for Ethiopia dressing these environmental problems in order to maintain the land to make agricultural activities more productive sustainably. For this, Sustainable Agricultural Intensification (SAI) offers workable options to eradicate poverty and hunger by improving the environmental performance of agriculture is the one.

Therefore, to address low soil fertility and soil moisture retention problems, maize and legume intercropping under conservation agricultural practices (i.e. minimum soil disturbance, crop rotation and crop residue retention) has been proposed as a sustainable intensification of food crop production which aims to increase resilience of maize-based farming systems to progressive climate change. The "Sustainable Intensification of maize-legume Farming Systems for Food Security in Eastern and Southern Africa (SIMLESA)" is an example of the pioneer effort led by The International Maize and Wheat Improvement Center (CIMMYT) and its partners in Eastern and Southern Africa with support from the Australian Centre for International Agricultural Research (ACIAR). The project is currently on-going in Kenya, Tanzania, Ethiopia, Malawi and Mozambique and targeting maize and five main legumes grown in the region (beans, pigeon pea, groundnut, cowpea and soybean).

In line of this, the ACIAR-led SIMLESA (Sustainable Intensification of Maize and Legumes in East and Southern Africa) program is helping farmers to test and adopt conservation agriculture methods using improved maize and legume varieties with different management practicies in southern Ethiopia in three Districts of Hawassa Zuria, Mesrak Badwacho and Meskan. Adoption of improved agricultural technologies has become a critical avenue of increasing productivity in developing countries, but is subjected to serious limitations. This paper therefore seeks to investigate and identifying the factors that affect adoption of SIMLESA technologies in the Southern Region of Ethiopia and thereby to provide some recommendations that can contribute to increase the use of these technologies and strengthen its impact for poverty reduction.

OBJECTIVES

The general objective of this study is to establish whether socio-economic factors that affect adoption of sustainable intensification of maize legume farming system in Easter and southern Africa (SIMLESA) project technologies on three Districts of southern Ethiopia. The specific objectives of the study include the following:

- To assess factors that affects the adoption of SIMLESA technologies.
- To generate information that enables to develop policy recommendations.

METHODOLOGY

Methods of Data Collection and Measurement

The study was carried out in Meskan, Mesrak Badwacho and Awassa Zuria districts of the South Nations Nationalities and Peoples Regional state (SNNPRS) of Ethiopia during December 2014 From each selected districts, 50 farm households were selected randomly from the sampling of SIMLESA technology users to make a sample size of 150 respondents. The Interview Schedule was developed to obtain relevant information that covering the overall objectives of the study. Interviews were conducted by means of Interview; the interview with farmers who were not fluent in Amharic (national language of the country) was done with the help of translator in order to preserve the accuracy of the information. In order to ascertain extent of adoption of improved technology, the responses of respondents were collected on five selected practices, namely Maize Bean intercropping, Crop rotation, Conservation agriculture, Maize variety (BH-543) and Legume variety (Awassa Dume).

Data Analysis

Model specification

In this study ordered logit model is employed to allow for multiple outcomes and scaling of multiple responses (Borooah 2001; Wooldridge 2001; Greene 2003). In estimating the adoption of SIMLEA technologies, it was felt that the multiple selections that the farm household faced are inherently ordered (MACO and ORGUT 2003). For this reason count models or any non-ordered model such as poisson regression and multinomial logit, respectively cannot adequately estimate the adoption of many choices as the information conveyed by the ordered nature is ignored resulting in loss of efficiency (Borooah 2001).

The proportional odds (PO) model, also called cumulative odds model (Agresti, 1996, 2002; Armstrong & Sloan, 1989; Long, 1997, Long & Freese, 2006; McCullagh, 1980; McCullagh & Nelder, 1989; Powers &Xie, 2000; O'Connell, 2006), is a commonly used model for the analysis of ordinal categorical data and comes from the class of generalized linear models. It is a generalization of a binary logistic regression model when the response variable has more than two ordinal categories. The proportional odds model is used to estimate the odds of being at or below a particular level of the response variable. For example, if there are *j* levels of ordinal outcomes, the model makes J-1 predictions, each estimating the cumulative probabilities at or below the *j*th level of the outcome variable. This model can estimate the odds of being at or beyond a particular level of the response variable as well, because below and beyond a particular category are just two complementary directions.

Before specifying the equation to estimate SIMLESA technologies, the approach used to order the practices is very crucial. Ordering practices requires care because "failure to impose a legitimate ranking on outcomes can introduce bias in estimates. This problem of biased estimates is more severe than treating categories as non-ordered since the latter may simply result in the loss of efficiency" (Borooah 2001). In an ordinal logistic regression model, the outcome variable is ordered, and has more than two levels. One appealing way of creating the ordinal variable is via categorization of an underlying continuous variable (Hosmer & Lemeshow, 2000).

In this study, adoption index was employed in order to categorize the possible outcomes orderly. According to Teha (2007), adoption index shows to what extent the respondent farmer has preserved the whole or proportion (intensity of adoption) was calculated based on the respondents score out of the given number of technology induced. Then after, the score was assigned for the adoption of each of the technology practices and weighted from hundred for each of the respondent households.

The total score for a respondent is obtained by summing up the score obtained on each practices. Therefore, the adoption level of the respondents was measured by making use of adoption index developed by Karthikeyan (1994).

$$Adoption\ Index = \frac{Respondents'\ Total\ Score}{Total\ Possible\ Score} \times 100$$

On the basis of adoption index formulated; the respondents were classified in to three categories as follows:-

1) Low adopters (up to 33%),
2) Partial adopters (34-66%) and
3) High adopters (67-100%).

Therefore, for this study, the ordinal outcome variable is the adoption of SIMLESA technologies, which is coded as 1, 2, or 3 (1 = low; 2 = partial; and 3 = high) and is categorized on levels of the independent variables(X_i):

- Age in years………………………….. (X_1)
- Education level in years ………………(X_2)
- Land size in hectare …………………...(X_3)
- Total livestock unit in number…………(X_4)
- Source of information ....(X_5)

Following to the relevant outcome description and variable specification, the model that is to be estimated is depicted as follows.

A Latent-Variable Model

The ordinal logistic regression model can be expressed as a latent variable model (Agresti, 2002; Greene, 2003; Long, 1997, Long & Freese, 2006; Powers &Xie, 2000; Wooldridge & Jeffrey, 2001). Assuming a latent variable, Y* exists, $Y^* = x\beta + \varepsilon$, can be defined where x is a row vector (1* k) containing no constant, β is a column vector (k*1) of structural coefficients, and ε is random error with standard normal distribution: ε ~ N (0, 1). Let Y* be divided by some cut points (thresholds): α1, α2, α3… αj, and α1<α2<α3…< αj. Considering the observed adoption of SIMLESA technology level is the ordinal outcome, y, ranging from 1 to 3, where 1= low, 2 = partial and 3 = high, define:

$$Y = \begin{cases} 1\ if\ y^* \le \alpha_1 \\ 2\ if\ \alpha_1 < y^* \le \alpha_2 \\ 3\ if\ \alpha_2 < y^* \le \infty \end{cases}$$

Therefore, the probability of farmers adoption level can be computed.

$P(y = 1) = P(y^* \le \alpha1)$
$= P(x\beta + \varepsilon \le \alpha1)$
$P(y = 2) = P(\alpha1 < y^* \le \alpha2)$
$= F(\alpha2 - x\beta) - F(\alpha1 - x\beta)$;
$P(y = 3) = P(\alpha2 < y^* \le \infty)$
$= 1 - F(\alpha_2 - x\beta)$;
The cumulative probabilities can also be computed using the form:

$P(Y \le j) = F(\alpha j - \mathbf{x\beta})$, where j = 1, 2,…J-1... (1)

General Logistic Regression Model

The logistic regression model can be expressed as:

$= \alpha + B_1X_1 + B_2X_2 + \ldots B_pX_p$.. (2)

In Stata, the ordinal logistic regression model is expressed in logit form as follows:

$\ln(Yj') = \text{logit}\ [\Pi(x)]$

$$= \ln\left(\frac{\Pi_j(x)}{1 - \Pi_j(x)}\right)$$

$= \alpha_j + (B_1X_1\ B_2X_2 - \ldots - B_pX_p)$,.. (3)

where $\Pi_j(\underline{x}) = \Pi(Y \le j|\ X_1\ X_2\ ,- \ldots - X_p)$, which is the probability of being at or below category j, given a set of predictors. j = 1, 2, … J -1. αj are the cut points, and B_1, B_2 …B_p are logit coefficients. This is the form of a Proportional Odds (PO) model because the odds ratio of any predictor is assumed to be constant across all categories. Similar to logistic regression, in the proportional odds model we work with the logit, or the natural log of the odds. To estimate the ln (odds) of being at or below the j^{th}category, the PO model can be rewritten as:

$\text{logit}\ [\Pi(Y \le j \mid x1,x2,\ldots xp)]$

$$= \ln\left(\frac{\Pi(Y \le j \mid x1, x2, \ldots xp)}{\Pi(Y > j \mid x1, x2, \ldots xp)}\right)$$

$=\alpha_j + (-B_1X_1 - B_2X_2 - \ldots - B_pX_p)$ ....(4)

Thus, this model predicts cumulative logits across J -1 response categories. By transforming the cumulative logits, we can obtain the estimated cumulative odds as well as the cumulative probabilities being at or below the j^{th}category.
The proportional odds model was fitted with all five explanatory variables. The assumption of proportional odds for both models was examined using the Brant test. The results of fit statistics, cut points, logit coefficients and cumulative odds of the independent variables of the models were interpreted and discussed.

RESULTS AND DISCUSSION

The analysis result of determinants of technology adoption from ordered logit model usingthe GLLAMM procedure in STATAversion 12 presented hereafter accordingly.

Ordered logistic regression

Table 1 reports results for the estimate of an ordered logistic regression model. The dependent variable is the adoption index of practicing a given SIMLESA technologies, where growers could arranged between categories of law adopter, partial adopter and high adopter against the explanatory variables of age, education level, total land size, tropical livestock unit and source of information used.

Table 1. Ordered logistic regression

LR chi2(5) = 59.83
Prob> chi2 = 0.0000
Log likelihood = -80.851201 Pseudo R2 = 0.2701

AI	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Age	.0426014	.0202991	2.10	0.036**	.002816	.0823869
Edu	.557132	.1108435	5.03	0.000 ***	.3398828	.7743812
Land size	-.0269253	.4076247	-0.07	0.947	-.825855	.7720043
TLU	.0747748	.0800043	0.93	0.350	-.0820307	.2315803
source	1.568556	.445467	3.52	0.000***	.6954571	2.441656
/cut1	1.999624	1.068569			-.0947328	4.093981
/cut2	4.457167	1.11481			2.272179	6.642155

, *** Significant at 5% and 1% respectively.

Based on the above output, the likelihood ratio chi-square of 59.83 with a p-value of 0.0000 tells us that our model as a whole is statistically significant, as compared to the null model with no predictors. The table 1 depicted above encompasses the coefficients, their standard errors, z-tests and their associated p-values, and the 95% confidence interval of the coefficients. Age, Education and Source of information are statistically significant; bothtotal land size and TLUare not. So for age, we would say that for a one unit increase in age, we expect a 0.04 increase in the log odds of being in a higher level of AI, given all of the other variables in the model are held constant. For a one unit increase in education, we would expect a 0.56 increase in the log odds of being in a higher level of AI, given that all of the other variables in the model are held constant. For a one unit increase in source, i.e., going from 0 to 1,we would expect a 1.57 increase in the log odds of being in a higher level of AI, given that all of the other variables in the model are held constant.The cutpoints shown at the bottom of the output indicate where the latent variable is cut to make the three groups that we observe in our data.

Table 2.Odds Ratio

Ordered logistic regression Number of obs = 150
LR chi2(5) = 59.83
Prob> chi2 = 0.0000
Log likelihood = -80.851201 Pseudo R2 = 0.2701

AI	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Age	1.043522	.0211825	2.10	0.036**	1.00282	1.085876
Education	1.745659	.1934949	5.03	0.000***	1.404783	2.169249
Landsize	.9734339	.3967957	-0.07	0.947	.4378605	2.164099
TLU	1.077641	.0862159	0.93	0.350	.9212437	1.260591
source of Information	4.799714	2.138114	3.52	0.000***	2.004625	11.49205
/cut1	1.999624	1.068569			-.0947328	4.093981
/cut2	4.457167	1.11481			2.272179	6.642155

, * Significant at 5% and 1% respectively.

The output of Table 2 above is the ordered logistic regression in terms of proportional odds ratios. The results are displayed as proportional odds ratios. For age, we would say that for a one unit increase in pared, the odds of high adoption versus the combined partial and low adoption categories are 1.04 greater, given that all of the other variables in the model are held constant. Likewise, the odds of the combined partial and high adoption categories versus low adoption are1.04 times greater, given that all of the other variables in the model are held constant. For a one unit increase in education, the odds of the high category of adoption versus the low and partial categories of adoption are 1.76 times greater, given that the other variables in the model are held constant. Because of the proportional odds assumption, the same increase, 1.76 times, is found between low adoption and the combined categories of partial and high adoption. For source, we would say that for a one unit increase in pared, i.e., going from 0 to 1, the odds of high adoption versus the combined partial and low adoption categories are 1.8 greater, given that all of the other variables in the model are held constant. Likewise, the odds of the combined partial and high adoption categories versus low adoption are4.8 times greater, given that all of the other variables in the model are held constant.

Proportional Odds Assumption

One of the assumptions underlying ordered logistic (and ordered probit) regression is that the relationship between each pair of outcome groups is the same. In other words, ordered logistic regression assumes that the coefficients that describe the relationship between, say, the lowest versus all higher categories of the response variable are the same as those that describe the relationship between the next lowest category and all higher categories, etc. This is called the proportional odds assumption or the parallel regression assumption. Because the relationship between all pairs of groups is the same, there is only one set of coefficients (only one model). If this was not the case, we would need different models to describe the relationship between each pair of outcome groups (Bruin, J. 2006).

Table 3. Brant Test of Parallel Regression Assumption

Variable	chi2	p>chi2	df
All	6.87	0.231	5
Age	0.16	0.688	1
Education	1.06	0.303	1
Land size	0.74	0.389	1
TLU	0.18	0.667	1
Source of information	6.52	0.011	1

Brant test can be used to test whether the proportional odds (i.e., parallel lines) assumption holds true. A significant test statistic provides evidence that the parallelregression assumption has been violated. The above tests indicate that we have not violated the proportional odds assumption

CONCLUSIONS AND RECOMMENDATIONS

This study examined factors that limit or facilitate SIMLESA technologies adoption among the farmers in the project intervention areas of Southern Ethiopia. Given the recent attention to intensification production methods favored by growers with an interest in sustainability, the findings of this study may contribute to ongoing efforts to promote the promoted technologies.

To understand the aspects influencing SIMLESA technologies usage in the project intervention areas, this study developed a theoretical model and examined key factor affecting the technology usage in Southern Ethiopia.

In the study area, the technology adoption is influenced by several key factors like age. The analysis result of this study revealed that as age of the farmers increases imply that the probability to adoption of the induced technologies will be raised significantly and positively.

Another important finding of our study is that education level, increased level of educationis more likely to adopt the technologies. Hence, educators and other relevant stakeholder should exert their efforts for the expansion of education and increase the participation of farmers in educationto increase likely of technologyadoption.

We also find thatSource of information is an important limiting factor to technology adoption. Utilization of Proper information dissemination Medias and those organizations working as source have a critical role to play in addressing technology adoption limitations. They could widely broadcast their information to ensure growers can make informed decisions on acquisition of the information about available technologies. Therefore, information suppliers can be useful for reaching large numbers of grower networks and can provide advice regarding appropriate information that could enhance the reliability of technology adoption .From the above findings it can be concluded that, Knowledge about improved technologies is essential for adoption of technologies. To increase the level of adoption of improved technologies knowledge about the new technology has to be improved by undertaking various extension approaches. Farmer's insight towards new technology is found to be an important element in determining the adoption of improved technologies. Therefore, Emphasis should be given devising a proper media for source of information acquisition and implementation in developing scientific mind and attitude of these technologies to increase their level of adoption.

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