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Factors Influencing the Agricultural Technology Adoption: The Case of Improved Rice Varieties (Nerica) in the Northern Region, Ghana

*Thomas Bilaliib Udimal[1] Zhuang Jincai[1, 2] Owusu Samuel Mensah[1] Ayamba Emmanuel Caesar[1]
1.School of Management, Jiangsu University, 301 Xuefu Road, Zhenjiang 212013, Jiangsu, P.R. China
2.Research Institute for New Rural Development, Jiangsu University, Zhenjiang 212003, P. R. China

Abstract
This paper analyses factors that influence the adoption of (Nerica) rice technology in the Northern Region of Ghana. Both logit and probit models were used in the analysis. The results from the two models are consistent with each other; they have similar signs for each variable but slight difference in the magnitude of the coefficients. Factors such as farm size, credit access, on-farm demonstration, tractor ownership, and family labor had positive influence on (Nerica) rice technology and statistically significant. The age, and profit orientation of the farmers had negative influence on the adoption on (Nerica) rice technology and statistically significant.
Keywords: Nerica rice; probit; logit; technology adoption; Northern Ghana.

1. Introduction

Increasing agricultural productivity is critical to meeting the continues rising demand for food. Agricultural technologies play immense role in increasing food productivity. As a result, it is useful to examine the adoption of technologies among farmers. Agricultural technologies are said to include all kinds of improved techniques and practices which affect the growth of agricultural output (Jain, Arora, & Raju, 2009). According to Loevinsohn, Sumberg, Diagne, and Whitfield (2013) the most common areas of technology development and promotion for crops include new varieties and management regimes; soil as well as soil fertility management; weed and pest management; irrigation and water management. According to Challa (2013) an improvement in input and output relationships, new technology tends to raise output and reduces average cost of production which in turn results in substantial gains in farm income.

A study by Kariyasa and Dewi (2013) indicate that the adoption of improved technologies increase productivity, which later results in socio-economic development. Adoption of improved agricultural technologies has been associated with higher earnings and a reduction in rural poverty among farm households; improved nutritional status; lower staple food prices; increased employment opportunities as well as earnings for landless laborers. Adoption of improved technologies is believed to be a major factor in the success of the green revolution experienced by Asian countries (Chen & Ravallion, 2004). A study by Jain et al. (2009) show that non-adopters of agriculture technologies can hardly maintain their marginal livelihood and are more prone to socio-economic stagnation which often results in deprivation.

A new agricultural technology that enhances sustainable production of food is therefore critical for sustainable food security and economic development. This has made the dynamics of technical change in agriculture to be an area of intense research since the early part of twentieth century(Jain et al., 2009).

These technologies are particularly relevant to smallholder farmers in developing countries because they are constrained in many ways, which makes them a priority for development efforts. These farmers for instance, live and farm in areas where rainfall is low and erratic, and soils tend to be infertile. In addition, infrastructure and institutions such as irrigation, input and product markets, and credit as well as extension services are poorly developed (Muzari, Gatsi, & Muvhunzi, 2012).

Over the years, studies have been conducted on innovation and adoption of new technologies in developing countries. In addition, the process of adoption and the impact of adopting new technology on smallholder farmers have been studied. However, this is not the case in the area of adoption of new varieties of crops and animals especially in Ghana. This paper therefore seeks to analyze the factors that influence farmer's adoption of improved (Nerica) rice technology; it is one of the few innovations that are introduced in the crop sub-sector to boost agriculture productivity.

2. Agriculture Technology adoption

Different authors define technology in different ways. According to Loevinsohn et al. (2013) technology is the means and methods of producing goods and services, including methods of organization as well as physical technique. Technology itself is aimed at improving a given status quo to a more desirable level. It assists the applicant to do work effectively and efficiently than he/she would have done in the absence of the technology (Bonabana-Wabbi, 2002).

Adoption is an integration of a new technology into existing practice and is usually proceeded by a period of 'trying' and some degree of adaptation (Loevinsohn et al., 2013). Adoption is in two categories; rate of adoption and intensity of adoption. The rate adoption is the relative speed with which farmers adopt an innovation, it time as one of its elements. Intensity of adoption refers to the level of usage of a given technology in any time period (Bonabana-Wabbi, 2002). According to (Doss, 2003) the first thing to consider is whether adoption is a discrete state with binary response variables or not. That means definition depends on the fact that the farmer is an adopter of the technologies or non-adopter taking values zero and one or the response is continuous variable (Challa, 2013).

The appropriateness of each approach depends on the particular context (Doss, 2003). Many researchers use a simple dichotomous variable approach in the farmers' decisions of new technology adoption. Therefore, researchers should clearly state how they are defining this term (technology adoption) so that they can develop appropriate tool to measure it.

2.1 Determinants of Agricultural Technology Adoption

According to Loevinsohn et al. (2013), a farmer's decisions about whether and how to adopt new technology are conditioned by the dynamic interaction between characteristics of the technology and the array of conditions and circumstances. Diffusion itself results from a series of individual decisions to begin using the new technology, decisions which are often the result of a comparison of the uncertain benefits of the new invention with the uncertain costs of adopting it (Hall and Khan, 2002). An understanding of the factors influencing this choice is essential both for economists studying the determinants of growth and for the generators and disseminators of such technologies (Hall and Khan, 2002).

Economic analysis of technology adoption has sought to explain adoption behavior in relation to personal characteristics and endowments, imperfect information, risk, uncertainty, institutional constraints, input availability, and infrastructure (Feder, Just, & Zilberman, 1985; Kohli & Singh, 1989; Koppel, 1995; Uaiene, Arndt, & Masters, 2009). In recent times literature has included social networks and learning in the categories of factors determining adoption of technology (Uaiene et al., 2009). A study by (Akudugu, Guo, & Dadzie, 2012) has grouped the determinant of agricultural technology adoption into three categories namely; economic, social and institutional factors.

Although there are many categories of factors influencing technology adoption, there is no clear distinguishing feature between variables in each category. Categorization is done to suit the current technology being investigated, the location, and the researcher's preference, or even to suit client needs (Bonabana-Wabbi, 2002). The level of education of a farmer has been classified as a human capital by some researchers while others classifies it as a household specific factor.

Human capital of the farmer is assumed to have a significant influence on farmers' decision to adopt new technologies. Most adoption studies have attempted to measure human capital through the farmer's Education, age, Gender, and household size (Fernandez-Cornejo et al., 2007; Keelan, Thorne, Flanagan, Newman, & Mullins, 2010). Education of the farmer has been assumed to have a positive influence on farmers' decision to adopt new technology. Education level of a farmer increases his ability to obtain; process and use information relevant to adoption of a new technology (Mignouna, Manyong, Rusike, Mutabazi, & Senkondo, 2011; Okunlola, Oludare, & Akinwalere, 2011). A study by (Okunlola et al., 2011) on adoption of new technologies by fish farmers found that the level of education had a positive and significant influence on adoption of the technology. This is because higher education influences farmers' decision, hence making them more open, rational and able to analyze the benefits of the new technology (Waller, Hoy, Henderson, Stinner, & Welty, 1998). This eases the introduction of a new innovation which ultimately affects the adoption process (Adebiyi & Okunlola, 2013). Other studies that have reported a positive relationship between education and adoption as cited by (Uematsu & Mishra, 2010) include; (Goodwin & Mishra, 2004) on forward pricing methods, (Huffman & Mercier, 1991); (Putler & Zilberman, 1988) on adoption of microcomputers in agriculture, (Mishra & Park, 2005)); (Mishra, Williams, & Detre, 2009) on use of internet on use of internet, (Rahm & Huffman, 1984) on reduced tillage,(Roberts et al., 2004) on precision farming and (Traore, Landry, & Amara, 1998) on on-farm adoption of conservation tillage.

On the other hand, some authors have reported insignificant or negative effect of education on the rate of technology adoption (Khanna, 2001; Samiee, Rezvanfar, & Faham, 2009). Studying the effect of education on technology adoption, (Uematsu & Mishra, 2010) reported a negative influence of formal education towards adopting genetically modified crops. Since the above empirical evidence have shown mixed results on the influence of education and adoption of new technology, more study need to be done in order to come up with a more consistent result. Age is also assumed to be a determinant of adoption of new technology. Older farmers are assumed to have gained knowledge and experience over time and are better able to evaluate technology information than younger farmers (Kariyasa & Dewi, 2013; Mignouna et al., 2011). On contrary age has been found to have a negative relationship with adoption of technology. This relationship is explained by (Mauceri, Alwang, Norton, & Barrera, 2005) that as farmers grow older, there is an increase in risk aversion and a decreased interest in long term investment in the farm. On the other hand, younger farmers are typically less risk-averse and are more willing to try new technologies.

Gender issues in agricultural technology adoption have been investigated for a long time and most studies have reported mixed evidence regarding the different roles men and women play in technology adoption (Bonabana-Wabbi, 2002). In analyzing the impact of gender on technology adoption, Morris and Doss (1999) had found no significant association between gender and probability to adopt improved maize in Ghana. They concluded that technology adoption decisions depend primarily on access to resources, rather than on gender. They further indicated if adoption of improved maize depends on access to land, labor, or other resources, and if in a particular context men tend to have better access to these resources than women, then in that context the technologies will not benefit men and women equally. Household size is simply used as a measure of labor availability. It determines adoption process in that, a larger household have the capacity to relax the labor constraints required during introduction of new technology (Mignouna et al., 2011).

Available information about the new technology influences its adoption. It enables farmers to know much about its existence as well as the effective use of technology and this facilitates its adoption. Farmers will only adopt the technology they are aware of or have heard about it. Access to information reduces the uncertainty about a technology's performance hence may change individual's assessment from purely subjective to objective over time. This simply implies that farmers may perceive the technology and subjectively evaluate it differently than scientists (Uaiene et al., 2009). Access to information may also result to dis-adoption of the technology. Where experience within the general population about a specific technology is limited, more information induces negative attitudes towards its adoption, probably because more information exposes an even bigger information vacuum hence increasing the risk associated with it (Bonabana-Wabbi, 2002). It is therefore important to ensure that information is reliable, consistent, and accurate. Farmers need to know the existence of technology, its beneficial, and its usage for them to adopt it.

Technology adoption among farmers is higher when extension services are made available. Through extension services, farmers get to know the benefits of new technology through extension agents. Extension agent acts as a link between the innovators (Researchers) of the technology and users of that technology. This helps to reduce transaction cost incurred when passing the information on the new technology to a large heterogeneous population of farmers (Genius, Koundouri, Nauges, & Tzouvelekas, 2013). Extension agents usually target specific farmers (farmers with whom a particular farmer interacts) exerting a direct or indirect influence overall population of farmers in their respective areas(Genius et al., 2013). Many authors have reported a positive relationship between extension services and technology adoption. A good example include; Adoption of Imazapyr-Resistant Maize Technologies (IRM) by (Mignouna et al., 2011). Factors determining technology adoption among Nepalese (Karki & Bauer, 2004) adoption of improved maize and land management in Uganda by (Sserunkuuma, 2005); adoption of modern agricultural technologies in Ghana (Akudugu et al., 2012) just to mention a few. This is because exposing farmers to information based upon innovation-diffusion theory is expected to stimulate adoption (Uaiene et al., 2009).

In fact, the influence of extension agents can counter balance the negative effect of lack of years of formal education in the overall decision to adopt some technologies (Yaron, Voet, & Dinar, 1992).

Access to credit has been reported to stimulate technology adoption (Mohamed & Temu, 2008). It is believed that access to credit promotes the adoption of risky technologies through relaxation of the liquidity constraint as well as through the boosting of household's-risk bearing ability (Simtowe & Zeller, 2006). This is because with an option of borrowing, a household can do away with risk reducing but inefficient income diversification strategies and concentrate on more risky but efficient investments (Simtowe & Zeller, 2006). However, access to credit has been found to be gender biased in some countries where female-headed households are discriminated against by credit institutions, and as such they are unable to finance yield-raising technologies, leading to low adoption rates (Muzari et al., 2012). There is therefore need for policy makers to improve current smallholder credit systems to ensure that a wider spectrum of smallholders are able to have access to credit, more especially female-headed households (Muzari et al., 2012). This may, in certain cases, necessitate designing credit packages that are tailored to meet the needs of specific target groups (Muzari et al., 2012).

Farm size plays a critical role in adoption process of a new technology. Many authors have analyzed farm size as one of important determinant of technology adoption. The adoption of technology by farmers is affected farm size and other factors influencing adoption affect farm size. Some technologies are termed as scale-dependant because of the great importance of farm size in their adoption (Bonabana-Wabbi, 2002). Many studies have reported a positive relation between farm size and adoption of agricultural technology (Uaiene et al., 2009; Wiggins, 2009). Farmers with large farm size are likely to adopt a new technology as they can afford to devote part of their land to try new technology unlike those with less farm size (Uaiene et al., 2009). In addition, lumpy technologies such as mechanized equipment or animal traction require economies of size to ensure profitability (Feder et al., 1985). Some studies have shown a negative influence of farm size on adoption of new agricultural technology. Small farm size may provide an incentive to adopt a technology especially in the case of an input-intensive innovation such as a labor-intensive or land-saving technology. Farmers with small land may adopt land-saving technologies such as green house technology, zero grazing among others as an alternative to increased agricultural production (Yaron et al., 1992). A study by (Grieshop, Zalom, & Miyao, 1988; Samiee et al., 2009) concluded that size of farm did not affect Integrated Pest Management (IPM) adoption implying that IPM dissemination may take place regardless of farmers' scale of operation. A study by (Kariyasa & Dewi, 2013) also found that extensive of land holdings had no significant effect on the degree of Integrated Crop Management Farmer Field School (ICM-FFS) adoption probability.

The above-mentioned studies considered total farm size and not crop acreage on which the new technology is practiced. Since total farm size has an effect on overall adoption, considering the crop acreage with the new technology may be a superior measure to predict the rate and extent of adoption of technology (Lowenberg-DeBoer, 2000). Therefore with regard to farm size, technology adoption may best be explained by measuring the proportion of total land area suitable to the new technology (Bonabana-Wabbi, 2002).

A key determinant of the adoption of a new technology is the net gain to the farmer from adoption, inclusive of all costs of using the new technology (Foster & Rosenzweig, 1995). The cost of adopting agricultural technology is a constraint to technology adoption. For instance, the elimination of subsidies on prices of seed and fertilizers since the 1990s due to the World Bank-sponsored structural adjustment programs in sub-Saharan Africa has widened this constraint (Muzari et al., 2012). Previous studies on determinants of technology adoption have also reported high cost of technology as a hindrance to adoption. The study done by (Makokha, Kimani, Mwangi, Verkuijl, & Musembi, 2001) on determinants of fertilizer and manure use in maize production in Kiambu county, Kenya reported high cost of labor and other inputs, unavailability of demanded packages and untimely delivery as the main constraints to fertilizer adoption. Cost of hired labor was also reported by (Ouma et al., 2002) as one among other factors constraining adoption of fertilizer and hybrid seed in Embu county Kenya. (Wekesa, Mwangi, Verkuijl, Danda, & De Groote, 2003) when analyzing determinants of adoption of improved maize variety in coastal lowlands of Kenya found high cost and unavailability of seeds as one of factors responsible for low rate of adoption.

Off farm, income has also been reported to have positive impact on technology adoption. This is because off-farm income acts as an important strategy for overcoming credit constraints faced by the rural households in many developing countries (Reardon, Stamoulis, & Pingali, 2007). Off-farm income is reported to act as a substitute for borrowed capital in rural economies where credit markets are either missing or dysfunctional (Ellis & Freeman, 2004). According to (Diiro, 2009) off- farm income is expected to provide farmers alternative source of liquid capital for purchasing productivity enhancing inputs such as improved seed and fertilizers. However not all technologies has shown positive relationship between off-farm income and their adoption. Some studies on technologies that are labor intensive have shown negative relationship between off-farm income and adoption. According to Goodwin and (Mishra & Park, 2005) the pursuit of off-farm income by farmers may undermine their adoption of modern technology by reducing the amount of household labor allocated to farming enterprises. This will did not limit itself to any category of factors but considered them in a holistic manner.

3. The Study Area and Sampling Techniques

In this study, the rice-growing districts in the Northern Region of Ghana were selected purposively for the research. The districts include; Savelugu, Tolon, Kumbungu, Saboba, Chereponi and Zabzugu. The region was selected because, that is where Savannah Agriculture Research Institute is located. The research sector is into crops and animals breeding. Face- to- face interviews with questionnaires were used to solicit response from the farmers.

A multi-stage sampling technique was used in selection the rice farmers for the study. Farmers who have been cultivation rice continuously for the past five years were purposively selected. This was to avoid new entrants in rice farming, since they may not have adequate knowledge about the varieties of rice that are available. After purposive sampling, simple random technique was used to select the required number of rice farmers for the interview. Fifty-seven rice farmers were selected from Savelugu, and fifty each from the remaining districts. Three-hundred and seven rice farmers were interviewed for the study. The field survey started in May and ended in July, 2016.

Table 1. Variable with their definitions and a prior expectation

Variables	Definitions	Expected signs
Age	Number of year	+/ -
Education	Years of formal education by the farmer	+
Credit access	1 if the farmer has access to credit; 0 otherwise	+
Tractor ownership	1 if the farmer owns any tractor or harvester; 0 otherwise	+
On- farm demonstration	1 if the farmer participated in any on-farm demonstrations; 0 otherwise	+
Family labor	No. of family members providing labor	+
Risk aversion	1 if the farmer practices crop diversification; 0 otherwise	+/-
Profit orientation	1 if the farmer treats rice farming as a business enterprise; 0 otherwise	+
Off farm income	Total income from sources other than rice farming in Ghana Cedi	+
Extension access	1 if the farmer access to advice from extension workers ; 0 otherwise	+
Surface water irrigation	1 if the farmer has an adequate source of water for irrigation; 0 otherwise	+
Farm size	Number of hectares used for rice	+

4. Theory and Empirical Model

Models for explaining a binary (1/0) dependent variable is based on either the respondent adopted (Y= 1) or does not adopt (Y= 0). It is assumed that a set of factors gathered in a vector x explain the decision, so that

$$\Pr o(Y = 1 \mid x) = F(x, \delta)$$
$$\Pr o(Y = 0 \mid x) = 1 - F(x, \delta) \quad (1)$$

The set of parameters δ reflects the impact of change in x on the probability. The problem at this point is to devise a suitable model for the right-hand side of the equation. One possibility in achieving that is to retain the familiar linear regression,

$$F(x,\delta) = x'\delta.$$

Since $E[y \mid x] = F(x,\delta)$, we can construct the regression model,

$$y = E[y \mid x] + (y - E[y \mid x]) = x'\delta + \varepsilon \quad (2)$$

The linear probability model has a number of shortcomings. A minor complication arises because ε heteroscedastic in a way that depends on δ. Since $x'\delta + \varepsilon$ must be within the range 1 0 or 1, the ε equals either $-x'\delta$ or $1 - x'\delta$, with probabilities $1-F$ and F, respectively. It can easily be revealed that

$$\operatorname{var}[\varepsilon \mid x] = x'\delta(1 - x'\delta) \quad (3)$$

The normal distribution has been applied in many analyses, giving rise to the probit model,

$$prob(Y = 1 \mid x) = \int_{-\infty}^{x'\delta} \varphi(t)dt = \lambda(x'\delta) \quad (4)$$

Also due to mathematical convenience and robustness, the logistic distribution (Greene, 2003),

$$\Pr ob(Y = 1 \mid x) = \frac{e^{x'\delta}}{1 + e^{x'\delta}} = \Lambda(x'\delta) \quad (5)$$

has also been applied in many analyses. Both logit and probit models are applied in this analysis. This is to compare the results from the two models to see if they actually make any significant difference. Adoption of a new technology is often explained as a function of its expected utility compared with that gained from the traditional technology using logit or probit models. In the present study, it is assumed that there are t choices available for the adoption of technology. While making a choice, it is assumed that an adopter's decision is influenced by his/ her utility maximization behavior. When the expected utility of the adoption of modern technology is higher than the expected utility of continuing with traditional technology, adopters decide to adopt modern technology.

The utility a farmer derives is random, which means that the utility derive from the adoption of rice variety technology may vary across individuals (i) at a particular point in time (t). The *ith* respondent adopts rice variety innovation, if he/she finds the expected utility of the adoption of rice variety innovation (A) is greater than non adoption i.e. $(U_{1i} > U_{0i})$. However, A* is not directly observable. A is equal to one, if a respondent adopt rice variety innovation, and 0 if the respondent does not, which is observable, i.e.,

$$\begin{cases} 1 \text{ if } A > 0 \\ 0 \text{ if } A \le 0 \end{cases}$$

The determinants of technology adoption in the industry is studied through the following logit model in which the dependent factor (modern technology adoption) is dichotomous i.e., adoption or not adoption.

P_i is assumed to be the probability that the rice variety innovation is adopted and, therefore, $1-P_i$ represents the probability of not adopting rice variety innovation (Gujarati & Porter, 1999). Thus, the logit model for the present analysis is specified as:

$$p_i = F(z_i) = F(\alpha + \delta x_i) = \frac{1}{[1+\exp(-z_i)]} \qquad (6)$$

where:

$F(z_i) =$ the value of the logistic cumulative density function associated with possible value of underlying index z_i

$p_i =$ the probability that an individual farmer would be willing to adopt *Nerica* rice technology given the independent variables as x_i

$\alpha =$ intercept

And $\delta x_i =$ the linear combination of independent variables.

$$z_i = \log\left[\frac{p_i}{(1-p_i)}\right] = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \dots + \delta_n x_n + \varepsilon \qquad (7)$$

where: $i = 1,2,\dots n$ observations

$z_i =$ the unobserved index level or the log odds of choice for the ith observation;

$x_n =$ the nth explanatory variable for the ith observation;

$\delta =$ parameter to be estimated; and

$\varepsilon =$ the error or the disturbance term.

The dependent variable z_i in the above equation is the logarithm of the probability that a particular choice will be made. The parameter estimates do not directly represent the effect of independent variables. For the continues variables, changes in the probability p_i and $y_i = 1$ as a result of the independent variable x_{ij} is given by;

$$\left(\frac{\partial p_i}{\partial x_{ij}}\right) = \frac{[\delta_j \exp(-\delta x_{ij})]}{[1+\exp(-\delta x_{ij})]^2} \qquad (8)$$

When some independent variables are also qualitative as in the case of this study the $\frac{\partial p_i}{\partial x_{ij}}$ does not exist. In that case the probability changes must be obtained by calculating the p_i at the alternative values of x_{ij} The probability changes are determined by the

$$\left(\frac{\partial p_i}{\partial x_{ij}}\right) = p_i(Y_i : x_{ij} = 1) - p_i(Y_i : x_{ij} = 0) \qquad (9)$$

The study is however silence on the specification of the probit model, but analyses has been done on it for comparative purposes.

The empirical is therefore stated as;

$$\textit{Adopted}\ \text{Nerica Rice Technology} = \delta_0 + \delta_1 age_1 + \delta_2 education_2 + \delta_3 creditaccess_3 + \delta_4 owntractor_4 + \delta_5 accesstoext_5 + \delta_6 surfacewaterirrig_6 + \delta_7 profitorientation_7 + \delta_8 farmsize_8 + \delta_9 familylabor_9 + \delta_{10} on-farmdemon_{10} + \delta_{11} off-far\min come_{11} + \varepsilon$$

Table 2 Descriptive statistic

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	307	47.29967	15.0969	19	77
Farm size	307	4.736971	2.137777	1	11
Education	307	3.983713	4.340461	0	16
Off-farm income	307	4894.56	4365.539	150	64300
Family labor	307	2.019544	2.181235	0	10

5. Discussion of results

From the table 2 above it is shown that the mean age of the rice farmers in the study area is approximately 47 years with 19 years been the minimum and 77 years the maximum. This shows that rice cultivation cut across the youth and the aged. The average farm size is approximately 5 hectares with one hectare been the minimum and sixteen hectares the maximum, an indication that rice farming is done at small-scale level.

On the educational level of the farmers, it was revealed that an average educational level of a farmer in the area is approximately primary four. There are farmers who had not received any form of formal education but the maximum educational level of farmers who had formal education is up to college level.

The table 3 below presents the results for both the logit and probit models. Because the coefficient result only tells the direction of change and not the probability or magnitude of change, marginal effects affects are analyzed and included in the table 4 below. The Prob > chi2 0.0000 for both models indicate that they are best fit than an empty model.

Age has a negative sign for both models, meaning as a farmer advances in age they turn to adopt less technologies as compared to the young farmers. This is because, as farmers grow older, there is an increase in risk aversion and a decreased interest in long-term investment in the farm. From the marginal effect, for logit model it is 5% for every unit increase in age and 6% for probit model for every unit increase in age. As a farmer advances in age their adoption rate for rice variety decreases by 5% and 6% for the logit and probit models respectively. They were both statistically significant at 1%. This result confirms a prior expectation for this study and agrees with study by (Mauceri et al., 2005) which indicate that older farmers are averse to technology adoption.

Table 3. Logit and Probit Coefficient Results

Adopted	(Logit Model)	(Probit Model)
age	-0.5658349***	-0.3135257***
	(0.1910527)	(0.992615)
Farm size	1.848706***	1.00189***
	(0.6991583)	(0.3569157)
Education	-0.3078441	-0.1671806
	(0.1754781)	(0.0870767)
Off-farm income	-0.0001554	-0.000082
	(0.000111)	(0.0000621)
Family labor	2.351795***	1.295901***
	(0.778721)	(0.3980952)
On-farm demonstration	5.32442**	2.900749**
	(2.195633)	(1.147157)
Access to extension	-3.867325	-2.154105
	(1.958057)	(1.102748)
surface water irrigation	0.3368334	0.103226
	(1.674478)	(0.9661033)
Own tractor	9.834188***	5.384285***
	(3.46487)	(1.801512)
Risk aversion	-1.888052	-1.044404
	(1.338814)	(0.7689662)
Profit orientation	-6.181859**	-3.513969**
	(2.545282)	(1.416372)
Credit access	8.347289**	4.704902**
	(3.464281)	(1.892777)
Constants	11.00393	6.299908
	(4.570895)	(2.532315)

Values in parenthesis are the standard errors.
*** Significant at 1%, ** significant at 5% and * significant at 10%.

The table 3 above shows, that farm size has a positive relation with the adoption of rice technology. Both models show a positive sign indicating that a unit increase in farm size with result in farmer's adoption of (Nerica) rice. This means (Nerica) rice technology should target farmers with large rice farms since they have the potential of adopting the technology. Farmers with large farm size are likely to adopt a new technology as they can afford to devote part of their land to try new technology which when successful would cause them to adopt the technology fully, unlike those with less farm size. The result on marginal effects in the table 4 below shows that a unit increases in farm size will result in about 17% and 20% chances of adopting the (Nerica) rice variety for logit and probit models respectively and statistically significant 1%. It is therefore, argued that farmers with large farms are wealthier than small-scale farmers, and can afford inputs that go with the technology adoption. In addition, since (Nerica) rice technology comes as a package, they are able to adopt the package than the smaller size farmers, especially fertilizer and other inputs requirement. This finding confirms the study by (Uaiene et al., 2009) which revealed that farm size influences farmers adoption of technologies.

The education and off-farm income in the table 3 above both have negative signs different from the expected, but they are not statistically significant. The coefficient of family labor in table 3 has a positive sign in relation to the adoption of (Nerica) rice. This implies that a farmer with family labor is more likely to adopt (Nerica) rice than those without family labor. The (Nerica) rice requires timely planting, prompt weeding and harvesting and all these activities are labor demanding, as a result farmers who are assured of labor are more likely to adopt than those that are not sure of their chances of getting labor. From table 4 below, the marginal effects it is revealed that farmers who have family labor are 22% and 26% for the logit and probit models respectively, chances of adopting the (Nerica) rice technology than those without family labor. This is statistically significant at 1%. The finding is consistent with the study by (Ouma et al., 2002) which indicated that the cost of labor is a hindrance to technology adoption. The availability of family labor is a relief to farmers since they can immediately rely on it in times of need hence its influence on technology adoption.

Farmers who have had opportunity to participate in on-farm demonstrations are more likely to adopt (Nerica) rice technology that their colleagues who have not had such opportunities. The results in table 3 above show that farmers who have participated in (Nerica) rice on-farm demonstration are more likely to adopt than others are. The results on the marginal effects in table 4 below show 69% and 66% for the logit and probit models respectively, chances of accepting the (Nerica) rice technology. Access to extension services and surface irrigation water were negative and positive signs respectively. They were both not statistically significant.

From the table 3 above, the ownership of tractor shows a positive influence on the adoption of (Nerica) rice technology. (Nerica) rice requires timely plowing, planting, and prompt weeding and harvesting and all these activities are labor demanding, as a result farmers who own tractors are able to do all these since their financial standing will be relatively better than those without tractors. The results from the table 4 below show that ownership of a tractor increases approximately 95% and 93% chances of adopting the (Nerica) rice technology for logit and probit models respectively. This is statistically significant at 1%. The result agrees with a prior expectations and the literature reviewed.

Profit orientation is postulate to have a positive influence on adoption of (Nerica) rice technology, but the findings from this study as indicated in table 3 above prove otherwise. The marginal effects in the table 4 show that, farmers who are mainly into rice farming for profit are 71% likely not to accept the (Nerica) rice technology as compared to those who just want to break-even. This percentage is the same for both models and statistically significant at 5%. The results on table 3 above show that access to credit has a positive influence on the adoption of (Nerica) rice technology. This can be because of risk associated with the adoption of the technology. The (Nerica) technology comes as a package and needed to be adopted in full to achieve the desire result. Farmer who is profit oriented may not adopt the technology if him/her is not sure of the ability to adopt every package associated with the technology.

The results from both models show that farmers who have access to credit are more likely to accept the (Nerica) rice technology relative to those without access. Credit to farmers enables them to purchase the inputs that are required in production hence its influence on farmer's adoption of (Nerica) rice technology. The results on marginal effects in the table 4 below show that access to credit gives farmers 88% and 87% chances of adopting the Nerica rice technology relative to those without access for logit and probit models respectively. This result confirms the finding by (Simtowe & Zeller, 2006) which indicates that access to credit promotes the adoption of risky technologies through relaxation of the liquidity constraint as well as through the boosting of household's-risk bearing ability.

Table 4. Marginal effects after logit pr(adopted)=0.89446267 and probit (adopted)= 0.88128891

Variable	dy/dx (logit)	dy/dx (probit
Age	-0.0534144	-0.0622417
Farm size	0.1745164	0.1988971
Education	-0.0290602	-0.033189
Off-farm income	-0.0000147	-0.0000163
Family labor	0.2220076	0.2572648
On-farm demon.	0.6850185	0.661132
Access to extension serv.	-0.4747191	-0.4834264
Surface water irrigation	0.032457	0.0206713
Own tractor	0.9480276	0.9439648
Risk aversion	-0.1704739	-0.1934056
Profit orientation	-0.7065793	-0.7062779
Credit access	0.878604	0.8743298

6.Conclusion and Recommendations

Both logit and probit models are suitable for studies on adoption. The choice of either model is left to the individual researcher and the assumptions made about the error term. Both models gave the same signs/direction of change; the differences in the coefficients are not much and could not alter the interpretation of the results.

The adoption of (Nerica) rice technology is influence by demographic characteristics, economic factors, and technical factors. Factors such as; age, farm size, on-farm demonstration, credit access, tractor ownership, family labor, and profit orientation of the farmers were found to have statistical significance in farmers' adoption of (Nerica) rice technology. Other factors such as; risk aversion, surface water irrigation, education, extension service contact, and off-farm incomes were not statistically significant.

Based on these findings we therefore recommend that introduction of new technologies to farmers should go hand in hand with on-farm demonstrations since it by that they would develop confidence and allay their fears associated with the technology. Credit schemes that are farmer friendly should be established to enable farmers have access to credit to facilitate their agricultural activities, since the adoption of technologies is largely depended on availability of input. Inputs such as fertilizer, tractor, and labor can easily be sourced when farmer have access to credit

It is also recommended that training sessions be offered to farmers, and builds their entrepreneurial skills, it is by so doing they will begin to consider their farming as business and adopt technologies that would increase productivity. New technologies should be directed to your and large scale farmers since they are more likely to adopt than aged farmers and small-scale farmers.

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Appendix

A1

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Adopted	1.0000												
2 Age	-0.7959	1.0000											
3 Farm size	0.3360	-0.2110	1.0000										
4 Education	0.0883	-0.1668	0.1832	1.0000									
5 Off-farm income	0.0761	-0.1191	0.1466	0.2854	1.0000								
6 Family labor	0.5809	-0.4453	0.2121	0.0915	0.0831	1.0000							
7 On-farm demonstration	0.3181	-0.3042	0.1013	0.0602	0.0653	0.1586	1.0000						
8 Access to ext	0.0813	-0.1266	0.1903	0.1816	0.2009	0.0159	0.1525	1.0000					
9 Surface water irrigation	0.0670	-0.0120	0.0972	0.1303	0.1065	0.0501	0.0069	0.0762	1.0000				
10 Own tractor	0.7981	-0.6375	0.2544	0.0670	-0.0246	0.4816	0.2754	0.1108	0.1045	1.0000			
11 Risk aversion	0.0337	-0.0427	0.0395	-0.0276	-0.0070	0.0108	0.0659	0.0174	0.0090	0.0319	1.0000		
12 Profit orientation	0.3287	-0.2407	0.2863	0.2414	0.2005	0.2631	0.2637	0.1750	0.1326	0.3222	0.1260	1.0000	
13 Credit access	0.6697	-0.5297	0.3624	0.2007	0.1696	0.4040	0.3323	0.1332	0.2415	0.5445	0.0245	0.3879	1.0000