ESTIMATION OF ACTUAL AND POTENTIAL ADOPTION RATES AND DETERMINANTS OF IMPROVED RICE VARIETY AMONG RICE FARMERS IN NIGERIA: THE CASE OF NERICAs

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Abstract

The article used the ATE estimation framework to derive consistent semi-parametric estimators of population adoption rates and their determinants of the NERICA (New Rice for Africa) rice varieties in Nigeria. Empirical evidence shows that the observed sample adoption rate does not consistently estimate the population adoption rate even if the sample is random. NERICA awareness was found to be a major constraint to NERICA adoption in Nigeria. Several socioeconomic/demographic characteristics were found to be important determinants of NERICA awareness and adoption. Among those factors are age, gender, major occupation, year of experience and vocational training. In particular, we have found that the NERICA adoption rate in Nigeria would have been up to 76% in 2008 instead of the actually observed 20% joint exposure and adoption rate, if the whole population were exposed to the NERICAs in 2008 or before. This justifies investing in the dissemination of the NERICA varieties; considering that the 76% is bound to increase significantly in the future as farmers learn more about the characteristics of the NERICAs and become comfortable with their performances.

Keywords: NERICAs Adoption, awareness, Average Treatment Effect, Nigeria

1. Introduction

Rice has become an important economic crop and the major staple food for millions of people in Sub-Sahara Africa in general and Nigeria in particular (WARDA, 2006). As a matter of fact, Africa has become a big player in international rice markets, accounting for 32% of global imports in 2006, at a record level of 9 million tones that year (WARDA, 2008). Africa's emergence as a big rice importer is explained by the fact that during the last decade, rice has become the most rapidly growing food source in sub-Saharan Africa (Solh, 2005). Indeed, due to population growth (4% per annum), rising incomes and a shift in consumer

preferences in favor of rice, especially in urban areas (Balasubramanian *et al.*, 2007), the relative growth in demand for rice is faster in this region than anywhere in the world (WARDA, 2005).

In Nigeria, the demand for rice has been increasing at a much faster rate than in other West African countries since the mid 1970s. For instance, during the 1960's, Nigeria had the lowest per-capita annual consumption of rice in the sub-region (average of 3 kg). Since then, Nigerian per-capita consumption levels have grown significantly at 7.3% per annum. Consequently, per-capita consumption during the 1980's averaged 18 kg and reached 22 kg in 1995-1999, by 2007 it was estimated at 27 kg and during this period, self-reliance had decreased from 87.4% to 71% (NBS, 2007). Despite the increase in per-capita consumption, Nigerian's consumption level is still lower than the rest of the sub-region (34 kg in 1995-1999). Estimated annual rice demand for Nigeria in 2009 is said to be 5 million tonnes, while production is said to average about 2.21 million tones. The national rice supply-demand gap of 2.79 million tones is expected to be bridged by importation (NRDS, 2009) which has constituted serious drain on the nation's foreign exchange.

Notwithstanding, in recent years, rice production has been expanding at the rate of 6% per annum in Nigeria, with 70% of the production increase due mainly to land expansion and only 30% being attributed to an increase in productivity (Fagade, 2000; Falusi, 1997; WARDA, 2007 and 2008; Okoruwa et. al., 2007). Much of the expansion has been in the rain fed systems, particularly the two major ecosystems that make up 78% of rice land in West and Central Africa (WCA): the upland and rain fed lowland systems (Dingkuhn *et al.*, 1997).

Yet, since area expansion and irrigation have already become a minimal source of output growth at a world scale, agricultural growth will depend more and more on yield-increasing technological change (Hossain, 1989). The adoption of new agricultural technology, such as the High Yielding Varieties (HYV), could lead to significant increases in agricultural productivity in Africa and stimulate the transition from low productivity subsistence agriculture to a high productivity agro-industrial economy (World Bank, 2008). In this regards, Mendola (2006) observed that the adoption of HYV had a positive effect on household wellbeing in Bangladesh.

New Rice for Africa (NERICA) is an interspecific hybrid between the local African rice (*Oryza glaberrima)* and the Asian rice (*Oryza sativa*) offers new opportunities for upland rice farmers. NERICAs have unique characteristics such as shorter duration (mature between 30 and 50 days earlier than traditional varieties), higher yield, and tolerance to major stresses, higher protein and good taste compared with the traditional rice varieties (Jones *et al*., 1997; Dingkuhn *et al*, 1998; Audebert *et al*, 1998; Johnson et al., 1998; Dingkuhn et al., 1999; Wopereis et al, 2008). NERICAs have also been reported to have stable yields under different management conditions and their introduction into farmers' fields was considered as a first step towards stabilization and sustainable intensification of Africa's fragile uplands rice. NERICA was introduced, on trial basis, in all West African countries including Nigeria since 2003 and have been enthusiastically adopted (WARDA, 2005).

To further enhance the adoption process of NERICA and also increase the production level of rice, Nigeria adopted several development initiatives, some of which including the African Rice Initiative (ARI) which was established in 2002 to promote the dissemination of NERICAs in several SSA, and the Presidential Initiative on increased rice production, processing and export launched in 2003 by the Federal Government of Nigeria. After about 6 years of dissemination and implementation, not much is known about the level of awareness (knowledge), adoption of NERICAs varieties among rice farmers in Nigeria. The empirical questions in this study are: 1) What is the actual and potential level of NERICAs adoption in Nigeria? 2) What are the factors affecting the adoption of NERICAs in Nigeria? 3) What are the determinants of awareness of NERICA among rice farmers in Nigeria?

Most studies have assessed the adoption rate of new technology or new programmes by simply computing the percentage of the adopter from the sample (see Nkonya et. al., 2007). This approach suffers either from what we call "nonexposure" bias or from selection bias. As a consequence, they generally yield biased and inconsistent estimates of *population* adoption rates even when based on a randomly selected sample. This study is necessary because it approaches the problem of estimation of adoption rates and their determinants from the perspective of modern evaluation theory as exposed in the treatment effect estimation literatures (see Angrist et al., 1996; Heckman et al., 1999; Imbens, 2004; Wooldridge, 2002).

2.   Methodology

2.1:   *Empirical framework*

Rogers (1962) defines adoption process as "the mental process an individual passes from first hearing about an innovation to final adoption". However, for rigorous theoretical and empirical analysis, a precise quantitative definition of adoption is needed. Such a definition must distinguish between individual (farm-level) adoption and aggregate adoption. Final adoption at the level of individual farmer is defined as the degree of use of a new technology in long-run equilibrium when the farmer has full information about the new technology and it's potential.

Classical approaches to the estimation of the determinants of adoption such as probit, logit and tobit models yield biased and inconsistent estimates even when based on a randomly selected sample. Therefore, to consistently estimate the NERICA population adoption rate and its determinants in Nigeria, we follow Diagne et. al. (2007, 2009) and use the Average Treatment Effect (ATE) estimation framework (see, for example, Imbens, 2004 for a review).

As pointed out by Diagne and Demont (2007) this approach is necessary because commonly used estimators of adoption rates suffer from either what is known as "non-exposure" bias or from "selection bias and yield biased and inconsistent estimates of population adoption rates even when based on a randomly selected sample. For the same reasons of population non-exposure and selection bias, the causal effects of the determinants of adoption cannot also be consistently estimated using simple probit, logit or tobit adoption models that do not control for exposure. The non-exposure bias also makes it difficult to interpret the coefficients of classical adoption models when the diffusion of the technology in the population is incomplete (Saha et al.1994, and Dimara and Skura, 2003). The true population adoption rate corresponds to what is defined in the modern treatment effect literature as the *average treatment effect,* commonly denoted by ATE. The ATE parameter measures the effect or impact of a "treatment" on a person randomly selected in the population (Wooldridge, 2002, chapter 18).

Following the modern treatment effect estimation literature (Diagne et. al., 2007; Wooldridge, 2002; Heckman, 1996; Angrist et. al., 1996; Rosenbaum and Rubin, 1983), we use a *counterfactual* outcome framework by which every farmer in the population has two

potential outcomes: with and without exposure to a technology. For concreteness and without loss of generality, we will focus on the adoption of new varieties (NERICA). Let y1 be the potential adoption outcome of a farmer when exposed to the new varieties and y0 be the potential adoption outcome when not exposed to them. The potential adoption outcome can be either adoption status (a dichotomous 0-1 variable) or a measure of intensity of adoption such as the total land area allocated to the new varieties. Then, the "treatment effect" for farmer *i* is measured by the difference $y_{i1} - y_{i0}$. Hence, the expected population adoption impact of exposure to the new varieties is given by the expected value $E(y_1 - y_0)$, which is, by definition, *the average treatment effect*, ATE.

But, the inability to observe both an outcome and its counterfactual makes it impossible in general to measure $y_1 - y_0$ for any given farmer. However, since exposure to a new variety is a necessary condition for its adoption, we have $y_0 = 0$ for any farmer whether exposed to the set of new varieties or not. Hence the adoption impact of a farmer *i* is given by y_{i1} and the average adoption impact is given by $ATE = Ey_1$. Unfortunately, we observe y_1 only for farmers exposed to the new varieties. Hence, we cannot estimate the expected value of y_1 by the sample average of a randomly drawn sample since some of the y_1 in the sample would be missing.

If we let the binary variable *w* be an indicator for exposure to the varieties, where $w = 1$ denotes exposure and $w = 0$ otherwise. The average adoption impact on the exposed subpopulation is given by the conditional expected value $E(y_1|w = 1)$, which is by definition the *average treatment effect on the treated*, commonly denoted by ATE1. Since, we do observe y_1 for all the exposed farmers, the sample average of y_1 from the sub-sample of exposed farmers will consistently estimate ATE1, provided the sample is random (see below). We can decompose ATE as a weighted sum of ATE1 and $E(y_1|w = 0)$, the expected adoption impact in the non-exposed subpopulation:

$$ATE = Ey_1 = P(w = 1) \times ATE1 + (1 - P(w = 1)) \times E(y_1|w = 0) \qquad (1)$$

Where $P(w = 1)$ is the probability of exposure. Hence, once we consistently estimate ATE, ATE1 and the probability of exposure, $P(w = 1)$, we can get from (1) the expected "non-exposure" bias $NBE = P(w = 1) \times ATE1 - ATE$; the expected bias from using the sample average adoption rate among the exposed $PSB = ATE1 - ATE$, and the expected adoption impact in the non-exposed subpopulation $E(y|w = 0) = \dfrac{ATE - P(w = 1) \times ATE1}{P(w = 0)}$

As usual, we can obtain the *observed* outcome y as function of the potential outcomes y1 and y_0 and the treatment status variable w as:

$$y = wy_1 + (1 - w)y_0 = wy_1 \qquad (2)$$

Where the second equality follows from the fact that y_0 is always equals to zero for adoption outcomes. Equation (2) shows in particular that the usually computed proportion of adopting farmers, $\dfrac{n_a}{n}$ (where $n_a = \sum_{i=1}^{n} y_i$ is the number of adopting farmers), is a consistent estimator of the joint probability of exposure and adoption $P(wy_1 = 1) = P(w = 1, y_1 = 1)$ and not in general a consistent estimator of the probability of adoption $P(y_1 = 1)$ even when the sample is random.

Similarly, a logit or probit model $P(y = 1|x) = F(x\beta)$, which has observed adoption status y as dependant variable and does not condition on *observed* exposure status variable w, will not yield consistent estimates of the coefficients of the determinants of *adoption*. At best it will yield consistent estimates of the effects of x on the joint probability of exposure *and* adoption, $P(w = 1, y_1 = 1|x)$. But such effect is not informative with regard to the effect of change in x on the conditional probability of adoption $P(y_1 = 1|x)$, which is in principle what a model of determinants of adoption seeks to elicit. Needless to say, the same remarks apply when the intensity of adoption is being modeled through the use of observed land used. We turn next to the estimation of the adoption rate and its determinants based on the observed random vectors $(y_i, w_i, x_i)_{i=1,2,...,n}$ from a random sample of the population.

The ATE methodology provides the appropriate framework for the consistent estimation of the population adoption rateand that of the determinants of adoption, which in this framework corresponds to the *conditional* ATE denoted usually as ATE(*x*). Wooldridge (2002, chapter 18) provides a succinct summary of the different estimators available for the consistent estimation of ATE. The ATE estimators are classified under two broad classes based on the assumption they require to be consistent. The first class of estimators is based on the conditional independence assumption. This assumption states that the treatment status *w* is independent of the potential outcomes y_1 and y_0 conditional on an observed set of covariates *x*. The second class of estimators is based on *instrumental variable* methods and assumes the existence of at least one instrument **z** that explains treatment status but is redundant in explaining the outcomes y_1 and y_0, once the effects of the covariates *x* are controlled for. The estimators using the conditional independence assumption are either a pure parametric regression-based method where the covariates are interacted with treatment status variable, or they are based on a two-stage estimation procedure where the conditional probability of treatment $P(w = 1|x) \equiv P(x)$, called the *propensity score*, is estimated in the first stage and ATE and ATE1 are estimated in the second stage by parametric regression-based methods or by non-parametric methods (including the so-called matching methods).

The Inverse probability weighting (IPW) estimator of ATE (nonparametric)

The weighting estimator is based on a two-stage estimation procedure where the conditional probability of treatment $P(w = 1|z) \equiv P(z)$, called the propensity score (PS), is estimated in the first stage and ATE, ATE1 and ATE0 are estimated in the second stage using the following probability weighting estimators which are special cases of the general weighting estimators of ATE, ATE1 and ATE0 when $y_0 = 0$ (Diagne and Demont, 2007):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n}\frac{y_1}{\hat{p}(z_i)} \qquad (1)$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n_e}y_i \qquad (2)$$

$$A\hat{T}E0 = \frac{1}{n - n_e} \sum_{i=1}^{n} \frac{(1 - \hat{p}(z_1))}{\hat{p}(z_i)} y_1 \qquad (3)$$

Where $\hat{p}(z)$ is a consistent estimate of the propensity score evaluated at z and $n_e = \sum_{i=1}^{n} w_i$ is the sample number of exposed farmers.

Parametric estimation of ATE

The parametric estimation procedure of ATE is based on the following equation that identifies $ATE(x)$ and which holds under the conditional independence (CI) assumption (see Diagne and Demont 2007):

$$ATE(x) = E(y_1|x) = E(y|x, w = 1) \qquad (4)$$

The parametric estimation proceeds by first specifying a parametric model for the conditional expectation in the right hand side of the second equality of equation (4) which involves the observed variables *y*, *x* and *w*:

$$E(y|x, w = 1) = g(x, \beta) \qquad (5)$$

where g is a known (possibly nonlinear) function of the vector of covariates *x* and the unknown parameter vector β which is to be estimated using standard Least Squares (LS) or Maximum Likelihood Estimation (MLE) procedures using the observations (y_i, x_i) from the sub-sample of exposed farmers only with *y* as the dependent variable and *x* the vector of explanatory variables. With an estimated parameter $\hat{\beta}$, the predicted values $g(x_i, \hat{\beta})$ are computed for all the observations *i* in the sample (including the observations in the non-exposed sub-sample) and ATE, ATE1 and ATE0 are estimated by taking the average of the predicted $g(x_i, \hat{\beta})i = 1,...,n$ across the full sample (for ATE) and respective sub-samples (for ATE1 and ATE0):

$$A\hat{T}E = \frac{1}{n} \sum_{i=1}^{n} g(x_i, \hat{\beta}) \qquad (6)$$

$$A\hat{T}E1 = \frac{1}{n_e} \sum_{i=1}^{n_e} w_i g(x_i, \hat{\beta}) \qquad (7)$$

$$A\hat{T}E0 = \frac{1}{n - n_e} \sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta}) \qquad (8)$$

The effects of the determinants of adoption as measured by the K marginal effects of the K-dimensional vector of covariates x at a given point $\bar{x}$ are estimated as:

$$\frac{\partial E(y_1 | \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k = 1, ..., K$$

Where x_k is the kth component of x.

2.2   Data and sturdy area

This study is based on a survey data collected in 2009 from three agro-ecological zones of Nigeria where NERICA dissemination activities were being conducted. A multistage sampling technique was used for the collection of the data. We stratified the sampling frame into three strata according to the main rice farming system practice in Nigeria: (i) upland; (ii) lowland; and (iii) irrigated rice. From each stratum, one state will be randomly selected. The second stage involved listing the Local Government Areas (LGA) and villages that practice rice farming in each state selected. We therefore selected 23 villages from Kano, 15 villages from Osun and 30 villages from Niger State. Both villages where NERICA varieties had been introduced and those where it were not yet introduced where selected. A total of 58 villages were selected and a total of 481 rice farmers were selected from the list of rice farmers in selected villages.

Evidence from table 1 reveals that majority of respondents (93.1%) where male. Also 90% of the adopters of NERICA were male. At the time of the survey, the average age of the farmers was 47 years. The average household size among respondents (both adopters and non adopters) was 10 people per family. 83.3% of respondents were native of their respective villages and in average have spent about 42 years in their villages. The educational level of

the household's head is significantly different between adopters and non adopters. About 68% of the adopters had at least primary school level while for non-adopters, only 42.1 % had at least primary school level. Also, there is a significant difference in the attendance of vocational training as well as in the type of experience in rice farming between adopters and non-adopters NERICA in Nigeria. We include in our set of characteristics a set of institutional characteristics, i.e. the percentage of farmers with access to extension services that is Nigerian Cereal Research Institute (NCRI) and Agricultural Development Programme (ADP). It appears that 24.6% and 8.9% of NERICA non adopters and adopters respectively reported having contact with either NCRI or ADP.

Table 1: Household socioeconomics characteristics by adoption status

Characteristic	Non-Adopters (n=378)	Adopters (n=101)	Total (n=479)	Difference
Socio-demographic factors	93.8	90.0	93.1	3.8
Proportion of male farmers (%)	6.2	10.0	6.9	3.8
Proportion of female farmers (%)	45	49	47	4
Age (average)	10	10	10	0
Household size (average)	83.6	82.3	83.3	1.3
% Born in the village	39	41	42	2
Number of years of residence in the village (average)				
Education and experience in rice farming				
% of no formal education	19.8	19.0	19.7	0.8
% of primary	21.7	36.0	24.7	14.3
% of secondary	16.9	31.0	19.9	14.1
% of post secondary school	3.5	1.0	3.0	2.5
Proportion of farmers that receive vocational training (%)				
Proportion of farmers with experience in low land rice farming (%)	8.0	31.8	12.7	23.8
Proportion of farmers with experience in upland land rice farming (%)	67.7	3.0	54.1	64.7
Proportion of farmers with experience in mangrove rice farming (%)	13.2	85.1	28.4	71.9
Institutional factors	19.0	6.9	16.5	12.1
Proportion of farmers in contact with NCRI				
Proportion of farmers in contact with ADP	10.6	1.0	8.6	9.6
	14.0	7.9	12.7	6.1

Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

3. Results and Discussions

Table 2 presents the result from probit estimation of the determinants of the probability of getting exposed to the NERICA variety. The log likelihood of -119.21 and the LRChi2 of 215.69 significant at 1% level show that the model is fitted. Three variables where found to be statistically significant at 1% level. These include: the number of years of experience in upland rice, gender of respondent and main occupation. The implication is that farmers with many years of experience in upland rice are more likely to know NERICA varieties than those that have few years of experience. Women are more likely to be exposed to NERICA than the men. The farmers that do not have agriculture as major activity were more likely to be exposed to NERICA than those that have agriculture as major activity. The marginal impacts show that for a 1% increase in the years of experience, the probability of adopting NERICA increases by 0.02%. (This implies a highly elastic response of 6.89 when evaluated at the mean values of the independent variables).

Table 2: Probit estimates of the determinants of the probability of exposure to the NERICA varieties

Variables	Estimated coefficients	Std. Err.	Marginal effect
Years of formal education (educ)	0.02	0.02	0.00
Number of years resident in the village (nbyres)	-0.01	0.01	-0.00
Osundum	0.60	0.52	0.15
Nigerdum	0.75	0.50	0.13
Years of experience in upland rice (Nbypup)	0.08	0.01***	0.02***
Household size (shhold)	0.03	0.03	0.01
Farmer native of the village (Farnatv)	-0.13	0.31	-0.03
Gender (sex)	-1.20	0.35***	-0.38**
ADPdum	-0.44	0.35	-0.07
NCRIdum	-0.63	0.50	-0.10
Main occupation (occup)	-1.57	0.26***	-0.49***
Constant	0.44	0.73	
Sample size	425		
LRchi2	215.69***		
Pseudo R^2	0.48		
Log Likelihood	-119.21		

*Legend: * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level*
Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

The ATE semi-parametric estimation of population adoption incidence rates presented in Table 3 show that all the parameters (with the exception of PSB) estimated with a robust Standard error were significant at 1 percent level. The full population adoption rate (ATE), which inform on the demand of the technology by the target population, is estimated to be 76%. This means that the NERICA adoption rate in Nigeria could have been 76% in 2008 instead of the actually observed 20% joint exposure and adoption rate, if the whole population were exposed to the NERICAs in 2008 or before. The corresponding estimates of the population adoption *gap* (i.e., the non-exposure bias), is 57%, and is statistically significantly different from zero at the 1% level. The adoption rate among the presently NERICA exposed subpopulation (ATE1) is estimated to be 86% while the estimated adoption rates for the non-exposed subpopulation (ATE0) is 73%. The estimated implied population PSB is 10% for the ATE semi-parametric which is statistically significantly different from zero at the 5% significance level. In other words, we reject the null hypothesis that the presently NERICA-exposed subpopulation is equally likely to adopt the NERICAs as the general population.

Table 3: ATE semi-parametric estimation of population adoption incidence rates

Adoption	Parameters	Robust Std. Err.	z	[95% Conf. Interval]	
ATE					
ATE	0.76	0.18	4.16***	0.40	1.12
ATE1	0.86	0.21	4.04***	0.45	1.28
ATE0	0.73	0.22	3.42***	0.31	1.16
JEA	0.20	0.05	4.04***	0.10	0.29
GAP	-0.57	0.17	-3.42***	-0.90	-0.24
PSB	0.10	0.21	0.49**	-0.30	0.50
Observed					
Ne/N	0.23	0.02	11.12***	0.19	0.27
Na/N	0.20	0.02	10.14***	0.16	0.23
Na/Ne	0.86	0.09	10.14***	0.70	1.03
Number of obs(N)	425				
Number of exposed (Ne)	96				
Number of adopters(Na)	83				

Legend: * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level
Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

The log likelihood of -95.15 and the LR chi2(13) of 205.36 significant at 1% level of significance show that the model is well fitted as all the explanatory variables together explain NERICA adoption among rice farmers. Parameter estimates from the probit analysis reveal age, number of years of experience in upland rice, major occupation, sex and vocational training as factors explaining NERICA adoption among rice farmers in Nigeria. These variables were significant at 5% level (Table 4).

It appears that increase in age or in number of years of experience in upland rice leads to increase in the likelihood to adopt NERICA. Also, farmers that have agriculture as major occupation have low likelihood to adopt than those that have other activities as major. Farmers that have received vocational training have higher probability to adopt than those who did not receive any. Women are more likely to adopt than their male counterpart. The empirical results can be explained by the fact that the ability to adapt new technology for use on a specific farm clearly influences the adoption decision. Greater years of education and/or experience is often hypothesized to increase the probability of adoption, whereas increasing age reduces the probability because of factors inherent in the aging process or the lowered likelihood of payoff from a shortened planning horizon over which accepted benefits can accrue (Fernandez-Cornejo *et al*., 1994; Barry *et al.,* 1995; Batte and Johnson, 1993). Younger farmers tend to have more education and are often hypothesize to be more willing to innovate. Another reason is that in agriculture the notion that technological innovations are perceived to be more risky than traditional practices have received considerable support in the literature. Many researchers argue that the perception of increased risk inhibit adoption (Feder *et al.,* 1985). When an innovation first appears, potential users are generally uncertain of its effectiveness and tend to view its use as experimental (Mansfield, 1966). Hiebert (1974) and Feder and O'Mara (1981, 1982) show that uncertainty declines with learning and experience thus inducing more risk-averse farmers to adopt an innovation, provided it is profitable.

Table 5: Probit models estimation of NERICA Adoption

Adoption	Coefficients	Std. Err.	z	Marginal effects
Farmers contact with ADP	0.11	0.41	0.26	0.019

Age	0.04	0.01	2.76***	0.006***
Years of education	0.02	0.03	0.62	0.003
Farmer native of the village	-0.15	0.36	-0.43	-0.028
Number of years of experience in upland rice	0.07	0.01	7.08***	0.012***
Number of years of residence in the village	-0.02	0.01	-1.39	-0.003
Farmer contact with NCRI	-0.54	0.50	-1.09	-0.068
Nigerdum	0.65	0.52	1.25	0.094
Occupation	-1.50	0.29	-5.14***	-0.427***
Osundum	-0.47	0.56	-0.85	-0.065
Sex	-0.94	0.41	-2.28**	-0.246*
Household size	0.01	0.03	0.50	0.003
Vocational training	0.60	0.29	2.03**	0.133
Constant	-0.91	0.84	-1.08	
Number of obs	409			
LR chi2(13)	205.36***			
Pseudo R2	0.5190			
Log likelihood	-95.15			

*Legend: * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level*
Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

4. Conclusion and Recommendations

In a world of perfect access to information, producers would be aware of and adopt new technologies that raise profits or well-being more generally (including convenience, leisure, utility, etc.). Awareness and adoption therefore would only depend on factors associated with profitability. That is, without informational constraints, the adoption decision would only depend on profitability. However, if there are informational constraints then adoption may also depend on awareness. This latter point is what is tested in this paper. In other words, are there farm operators for whom this technology is profitable but who are not aware of its existence?

NERICA awareness was found to be a major constraint to NERICA adoption in Nigeria. Factors such as age, gender, major occupation, year of experience and vocational training were found to be important determinants of NERICA awareness and adoption. The above socioeconomic/demographic characteristics were found to be important determinants of NERICA awareness and adoption. Among those factors are age, gender, major occupation, year of experience and vocational training. In particular, we have found that NERICA adoption rate in Nigeria would have been up to 76% in 2008 instead of the actually observed 20% joint exposure and adoption rate, if the whole population were exposed to the NERICAs in 2008 or before. This justifies the investment made in the dissemination of the NERICA varieties; considering that the 76% of potential adopters is bound to increase significantly in the future as farmers learn more about the characteristics of the NERICAs and become comfortable with their performances.

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