Estimation of Actual and potential adoption rates and determinants of a new technology not universally known in the population: The case of NERICA rice varieties in Guinea

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ABSTRACT

The paper uses the Average Treatment Effect (ATE) estimation framework and data from a sample of 1467 rice farmers in Guinea to document the *actual* and potential adoption rates of NERICA varieties and their determinants in Guinea, a country reported to have seen the largest number of adopting farmers among the SSA countries. The results of the analysis indicate that only 37% of the sample households were exposed to NERICA rice varieties in 2001 and that 20% of the sampled rice farmers adopted NERICA The potential adoption rate for the population is estimated at 61% with the adoption gap (difference between the 61% potential adoption rate and the 20% actual adoption rate) resulting from the incomplete exposure of the population to the NERICA varieties estimated at 41%. The findings suggest a relatively large unmet demand for the NERICA varieties in Guinea that justify investment in its further dissemination in Guinea.

Key words: *NERICA varieties, Technology Diffusion and adoption,, Average Treatment Effect, Guinea*

1 Introduction

Africa has the highest growth rate in the demand for rice estimated at 6% while its rice self sufficiency ratio, currently at 61%, has been on a decline such that in 2006 Africa relied on the international market to satisfy about 40% of its rice consumption needs (WARDA, 2007). Yet, Africa can turn the increasing rice price to a unique historical opportunity to realize the latent potential for rice production. It is widely acknowledged that an improvement in crop productivity, based on new varieties is a foundation for the potential *Green Revolution* in developing countries (Evenson, 2002) and that the increased use of improved rice technologies by farmers could potentially reverse the currently declining trend in rice self sufficiency.

The Africa Rice Centre developed new high yielding rice varieties in the mid 1990s, which have been dubbed "New Rice for Africa" (NERICA). The NERICA (New Rice for Africa) rice varieties are the result of inter-specific crosses between the *Oryza sativa* high yielding rice species from Asia and the locally adapted and multiple-stress resistant *Oryza glaberrima* African rice species developed by the Africa Rice Center (WARDA) during the 1990s (Jones et al. 1997). With their high yield potential and their adaptability to African conditions, the NERICA varieties are providing hopes for raising the productivity of upland rain-fed rice farming in Africa characterized by a very low use of modern inputs (Dingkuhn et al. 1998, Johnson et al. 1998)[1] . According to the March 2008 FAO Rice monitor the NERICA adoption by an increasingly large number of farmers is believed to have contributed to the six percent total increase in Africa's rice output in 2007.

While there exists evidence of positive impacts of the NERICA varieties on productivity and poverty (Kijima, et al. 2008 and 2006; Diagne et al., 2008; Diagne, 2007; Adégbola et al., 2007; Adekambi et al., 2008a and 2008b; Agboh-Noameshie et al., 2008), the *actual* adoption rates of the NERICA varieties remain relatively low in all the countries because of a low diffusion rate in the rice farming population (i.e. many farmers are not aware of the existence of the varieties) and an extremely limited supply of its seed. For example, Diagne (2006) reports that only 10% of the farmers surveyed in Cote d'Ivoire were aware of the NERICA rice varieties in 2000 and as a result the actual sample adoption rate was merely 4%. A response to the aforementioned problem of low adoption has been the initiation of several country as well as regional-based initiatives to promote the diffusion and adoption of NERICA varieties and other improved varieties.

The NERICA varieties were introduced to rice farmers in Guinea in 1997 through Participatory varietal selection (PVS) and on-farm research trials (WARDA, 1999). Farmers then started disseminating them

[1] The NERICA rice varieties won its creator Monty Jones the 2004 World Food Prize and his inclusion in the 2007 Time magazine's list of the 100 most influential people in the world.

through their informal channels. Since 1997, a number of NERICA varieties have been disseminated in Guinea but the entire population has not yet been exposed to the technology, despite the fact that Guinea is cited as a country where the dissemination of NERICA varieties has been most successful. Furthermore, the dissemination of NERICA varieties was done in a few non-randomly selected villages across the different agro-ecological zones. As pointed out by Diagne and Demont (2007), Dimara and Skuras (2003), Besley and Case (1993) and Saha et. al., (1994), under incomplete exposure, and non-random dissemination of a technology, it is impossible to obtain consistent estimates of population adoption rates and their determinants using direct sample estimates and classical adoption models such as probit or tobit. In this paper, we use the Average Treatment Effect (ATE) estimation framework and survey data from Guinea to provide estimates of the actual and potential NERICA adoption rates and determinants in Guinea.

The paper is organized as follows: Section 2 presents the ATE framework for estimating adoption rates and their determinants. Section 3, describes briefly, the dissemination of the NERICA varieties in Guinea and presents the sampling methodology and the data. The Results and discussions are presented in section 4, while section 5 concludes the paper.

2 ATE estimation of NERICA adoption rates in Guinea

A number of NERICA varieties have been disseminated in Guinea but the entire population has not yet been exposed to the technology. Furthermore, the dissemination of NERICA varieties was done in a few non-randomly selected villages across the different agro-ecological zones. When a technology is new and the target population is not universally exposed to it, the observed sample adoption rate is not a consistent estimator of the true potential population adoption rate. Likewise, classical approaches to the estimation of the determinants of adoption (e.g. probit 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 Guinea we follow Diagne and Demont (2007) 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 (Besley and Case, 1993 Saha et al.1994, and Dimara and Skura, 2003).

The non-exposure bias results from the fact that farmers who have not been exposed to a new technology cannot adopt it even if they might have done so if they had known about it (Diagne 2006). This fact leads to the observed sample adoption rate to always underestimate the true population adoption rate when exposure of the population to the new technology is incomplete. However, as noted by Diagne (2006) the underestimation diminishes and eventually vanishes when the exposure of the population to the new variety is complete.

The sample adoption rate within the sub sample of farmers exposed to the technology is also not a consistent estimate of the true population adoption rate (even if the sample is random). In fact, the sample adoption rate among the exposed is likely to overestimate the true population adoption rate because of a positive population selection bias by which the subpopulation most likely to adopt gets exposed first. The sources of positive selection bias include farmers' self selection into exposure and the targeting of progressive farmers by researchers and extension workers (Diagne 2006).

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). In the adoption context "treatment" corresponds to exposure to a technology and the ATE on the adoption outcomes of population members is the population mean adoption outcome. This is the population mean adoption outcome when all members of the population have been exposed to a technology and it is, therefore, a measure of the intrisinc value of the technology as indicated by its potential demand by the population. In that sense, the population mean adoption outcome measured by the ATE parameter is the population mean *potential* adoption. The difference between the population mean potential adoption outcome and the population mean actual (i.e. observed) adoption outcome, which is in fact the combined mean of population exposure to and adoption of the technology, is the population non-exposure bias, also known as the population adoption gap, which exists because of the incomplete diffusion of the technology in the population. Similarly, the mean adoption outcome in the exposed subpopulation corresponds to what is defined in the treatment effect literature as the *average treatment effect on the treated,* (i.e. the mean effect of a treatment in the treated subpopulation), commonly denoted as ATE1 or ATT (Wooldridge, 2002, chapter 18). The difference between the population mean adoption outcome (ATE) and the mean adoption outcome among the exposed (ATE1) is the population selection bias (PSB).The consistent estimation of ATE and ATE1, which are the main focus of the treatment effect methodology, requires controlling appropriately for the exposure status. The details of the estimation procedures of the ATE parameters in the adoption context are given below.

Under the ATE estimation framework it is assumed that every farmer in the population has two *potential* adoption outcomes: with and without exposure to a technology (the treatment). Let us assume w to be a binary variable indicating the observed status of exposure to at least one NERICA variety, where $w = 1$

if the farmer is exposed and $w = 0$ if the farmer is not exposed. Let y_1 be the *potential* adoption outcome of a farmer when exposed (i.e. when *w*=1 for him or her) and y_0 is his or her potential adoption outcome when not exposed (i.e. when *w*=0 for him or her). The *observed* adoption outcome y can be expressed as a function of the two potential adoption outcomes y_1 and y_0 and the treatment status variable w as $y = wy_1 + (1 - w)y_0$. The population mean impact of exposure to the NERICA varieties on population adoption outcomes is given by the expected value $E(y_1 - y_0)$, which is by definition the average treatment effect (ATE) of exposure.

Because exposure to the NERICA varieties is a necessary condition for their adoption, we have $y_0 = 0$ for any farmer whether exposed to the NERICA varieties or not. Hence, in this adoption context, ATE is reduced to the expected value $E(y_1)$ which is the population mean potential adoption outcome. The exposed subpopulation mean potential adoption outcome is given by the conditional expected value $E(y_1 \mid w = 1)$, which is by definition ATE1, the average treatment effect (of exposure) on the treated. Similarly, the non exposed (untreated) subpopulation mean potential adoption outcome denoted by ATE0 is given by $E(y_1 \mid w = 0)$. Also, with $y_0 = 0$ the expression of the observed adoption outcome variable as a function of the two potential adoption outcomes and the exposure variable reduces to $y = wy_1$, an expression that shows clearly that the observed adoption outcome variable is a combination of the exposure *and* adoption outcome variables. This justifies calling the population mean *observed* adoption outcome $E(y) = E(wy_1)$ the population mean joint exposure and adoption parameter denoted as JEA to differentiate it from the population mean adoption parameter $E(y_1)$, which as we know is ATE and a measure of the potential demand of the technology by the population in terms of adoption. The difference between the JEA and ATE parameters (i.e. the difference between the population mean *observed* adoption outcome and the population mean *potential* adoption outcome) is the population non exposure bias (NEB), also called the population adoption gap (GAP): $NEB = GAP = E(y) - E(y_1)$. The population selection bias (PSB) defined as the difference between the mean potential adoption outcome in the exposed subpopulation and the mean potential adoption outcome in the full population is given by: $PSB = ATE1 - ATE = E(y_1 \mid w = 1) - E(y_1)$.

We should note that when the adoption outcome variable is a binary variable taking the values 0 and 1 (i.e. a measure of adoption status with 1 corresponding to adoption), as is the case in our empirical analysis, then the expected values corresponding to the various population mean adoption outcomes reduce to probability quantities that correspond to measures of population adoption *rates* (i.e. proportions of adopting farmers in the population). In particular, $ATE = E(y_1) = P(y_1 = 1)$ corresponds to the population potential adoption rate, $ATE1 = E(y_1 \mid w = 1) = P(y_1 = 1 \mid w = 1)$ to potential adoption rate in the exposed subpopulation and ATE0 $= E(y_1 \mid w = 0) = P(y_1 = 1 \mid w = 0)$ to the potential adoption rate in the non exposed subpopulation.

The ATE methodology enables the identification and consistent estimation of the population mean adoption outcome $E(y_1)$ and the population mean adoption conditional on a vector of covariates x $E(y_1 \mid x)$, which in this framework corresponds to the *conditional* ATE denoted usually as ATE(x) (Wooldridge 2002 chapter 18). One approach to the identification of ATE is based on the so-called conditional independence assumption (Wooldridge 2002, chapter 18) which states that the treatment status w is independent of the potential outcomes y_1 and y_0 conditional on the observed set of covariates z that determine exposure (w). The ATE parameters identified through the conditional independence assumption can be estimated from a random sample of observed $(y_i, w_i, x_i)_{i=1,..,n}$ in two different ways:[2] 1) using a weighting estimator and 2) using an estimator based on a parametric regression procedure.

The Inverse probability weighting (IPW) estimator of ATE

The weighting estimator is based on a two-stage estimation procedure where the conditional probability of treatment $P(w = 1 \mid z) \equiv P(z)$, 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):

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

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

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

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.[3]

[2] One can also use a Matching based estimator (see, for example, Imbens, 2004).

[3] The weighting estimators for the general case are based on the following results that identify ATE, ATE1 and ATE0: $ATE = E\left(\frac{(w - p(z))}{p(z)(1 - p(z))} y\right)$, $ATE1 = \frac{1}{P(w = 1)} E\left(\frac{(w - p(z))}{1 - p(z)} y\right)$ and $ATE0 = \frac{1}{1 - P(w = 1)} E\left(\frac{(w - p(x))}{p(z)} y\right)$ (see, for example, (Lee, 2005, pp. 65-70; Imbens, 204; and Wooldridge,

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):

$$ATE(x) = \mathrm{E}(y_1 \mid x) = \mathrm{E}(y \mid x, w = 1) \quad \textbf{(4)}$$

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*:

$$E(y \mid x, w = 1) = g(x, \beta) \qquad \textbf{(5)}$$

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 subsample 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 subsample) 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 subsamples (for ATE1 and ATE0):

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

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

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

2002, p.). When the fact that $wy = y$ (which follows from the fact that $y = wy_1$) is used, we get the simplifications that lead to the sample analogue estimators in equations (1), (2) and (3). The propensity score $p(z)$ can be consistently estimated using non-parametric methods or using parametric methods such as probit or logit models (see Imbens, 2004). We note that the weighting estimator for ATE1 is simply the proportion of adopters in the exposed subsample and does not depend on the estimated propensity score $\hat{p}(z_i)$. Also, implicit in the weighting estimators is the requirement that $0 < \hat{p}(z_i) < 1$ and $0 < n_e < n$.

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:

$$\frac{\partial E(y_1 \mid \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k = 1,..,K \quad \textbf{(9)}$$

where x_k is the k^{th} component of x.

In our empirical analysis below, we have estimated the ATE, ATE1, ATE0, the population adoption gap ($G\hat{A}P = J\hat{E}A - A\hat{T}E$)[4], and the population selection bias ($P\hat{S}B = A\hat{T}E1 - A\hat{T}E$) parameters using both the inverse probability weighting (IPW) estimators (equations 1, 2, and 3) and the parametric regression based estimators (equations 4,5, and 6). The propensity score $\hat{P}(z)$ appearing in the IPW estimators is estimated using a probit model of the determinants of exposure: $P(z) = \Phi(z\gamma)$ where Φ is the standard normal cumulative distribution with density function $\phi(t) = (1/\sqrt{2\pi})\exp(-t^2/2)$, z the observed vector of covariates determining exposure to the NERICA varieties and γ is the parameter vector being estimated. This estimation of the determinants of exposure is important for its own sake as it can provide valuable information regarding the factors influencing farmers' exposure to a new technology. These factors, which are mostly related to the diffusion of information, can very well be different from those influencing the adoption of the technology once exposed to it. For the parametric regression based estimators, since y is a binary variable in our empirical analysis, the equation 5 above is effectively a parametric probabilistic model as we have discussed earlier. That is, we have $E(y \mid x, w = 1) = P(y = 1 \mid x, w = 1)$ with, assuming a probit model, $g(x, \beta) = \Phi(x\beta)$. Thus, in this particular case the parametric estimation of ATE reduces to a standard probit estimation restricted to the exposed sub-sample. The marginal effects in equation (9) are also estimated using this ATE parametric model.[5] For comparison purposes, we have also estimated a "classic" probit adoption model (which, as discussed above is in fact a model of the determinants of joint exposure and adoption): $P(y = 1 \mid x') = \Phi(x'\theta)$ where $x' = (z, x)$ is the vector of covariates determining both exposure (w) and adoption (y_1) and θ is the parameter vector to be estimated.[6] All the estimations were done in Stata

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[4] Note that as discussed earlier, the joint exposure and adoption parameter (JEA) is consistently estimated by the sample average of the *observed* adoption outcome values: $J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} y_i$.

[5] Note that the marginal effects of the determinants of adoption (i.e. the effects of the marginal changes in the vector of covariate x) cannot be estimated from the IPW based estimators.

[6] We should note that usually the two vectors z and x have common elements so that the dimension of the vector x' is usually less than the sum of the dimensions of its two components. It is clear that not including in the vector x' determinants of w not in x will most likely result in the non-identification of "classic" adoption model. However, in practical estimation terms the main difference between the ATE parametric adoption model and the "classic"

using the Stata add-on *adoption* command developed by Diagne (2007) to automate the estimation of ATE adoption models and related statistical inference procedures (see).[7] The asymptotic distributions of $A\hat{T}E$, $A\hat{T}E1$ and $A\hat{T}E0$ are given in Lee (2005, pp. 67-69) for the general case where $y_0 \neq 0$ and $p(z)$ is estimated through a probit model

3 The Dissemination of NERICA rice varieties in Guinea and description of the data

3.1 Dissemination of NERICA rice varieties in Guinea

Guinea is divided into eight regions which are subdivided into four agro-ecological zones, namely Lower, Upper, Forest and Middle guinea. The eight regions are further subdivided into 33 *prefectures*[8]. Rice farming is characterized by four production systems, namely: rain fed rice-farming (rain fed, upland and mountain areas), plains rice-farming (rain-fed and flood plain), lowland rice-farming, and mangrove rice-farming. Although farmers may practice more than one rice farming system in the same agro-ecological zone, upland rain-fed rice farming is the most predominant in Guinea accounting for 69% of the cultivated rice area (Barry and Conde, 1999).

The dissemination of NERICA varieties in Guinea started in 1997. The new varieties were introduced in the major rice growing areas and systems. Between 1997 and 1998, NERICA varieties underwent field tests in farmer experimental plots (UEP)[9] managed by the farmers and supervised by research and extension, and also in plots under Participatory Varietal Selection (PVS) managed by research. PVS trials were undertaken for three years from 1997 to 1999. As a result of these various trials on farmer fields and on research stations, about 34 inter-specific varieties and 304 other improved varieties were introduced between 1997 and 1998. Six new rice varieties were introduced by the UEPs, including three varieties

adoption model lies in the fact that the latter uses *all* the sample observations while the latter uses the observations from the exposed sub-sample only.

[7] The *adoption* command is a Stata add-on command that works like standard Stata regression commands. It uses various Stata standard estimation commands internally to implement the estimation procedures described above and, depending on the option chosen, provide IPW or parametric regression based estimates of ATE, ATE1, ATE0, JEA, GAP and PSB. The option include the choice of functional form for the propensity score (probit or logit) and the function $g(x,\beta)$ described above. The advantage of using the *adoption* command (instead of directly using the standard Stata commands) is that it provides the standard errors (and related confidence intervals and p-values) of all above estimated ATE parameters directly in a standard Stata estimation results table. The standard errors of the IPW-based estimators are based on the derivation of asymptotic distributions of $A\hat{T}E$, $A\hat{T}E1$ and $A\hat{T}E0$ given in Lee (2005, pp. 67-69) specialized to the adoption case (with provision covering the case where the propensity score is estimated by a logit model). The standard errors (and related confidence intervals and p-values) of the parametric regression based estimators are obtained by using the delta method (Wooldridge, 2002, p.44) to derive the asymptotic distribution of the ATE estimators in equations 4 to 6. The *adoption* command also includes Stata style post-estimation commands (in addition to the ones corresponding to the internally used Stata estimation commands) that provide the same ATE estimates as above for any defined subgroup in the population and marginal effects for the estimated exposure and adoption models (with options not available with the Stata standard *mfx* command)

[8] A French name, which implies a sub- region in Guinea's major regions.

[9] It is a French acronym which stands for "Unité Expérimentale Paysanne" which means "farmer-experimental Trials"

from WARDA[10], one variety developed by IRAG, one variety representing the most cultivated variety in the agro-ecological zone, and lastly one of the varieties cultivated by the farmer who had hosted the experimental unit. Eight *prefectures* (Macenta, N'zérékoré and Beyla in Forest Guinea; Faranah in Upper Guinea; Télimélé, Forécariah and Boké in Maritime Guinea; and Koundara in Middle Guinea) hosted these units in 1997, and 15 hosted them in 1998. In 1997, eight *prefectures* in the country were host to experimental units. According to the Guinea ministry of agriculture and livestock (2002), Guinea's rapid increase in the hectares allocated to NERICA varieties to several thousands by 2003 is attributed to a number of reasons and they include 1) the importance of rice as a main staple food in Guinea; 2) the willingness and commitment of the Guinean Government to make rice production a priority for achieving food security, 3) the multi-institutional interest – (with an initial push coming from the World bank and WARDA) and collaborative efforts put in place by different departments of the Guinean Ministry of Agriculture, 4) the introduction and strict application of new approaches to the transfer of technologies adopted by WARDA, the World Bank and Guinean NARES , 5) the additional support to Research and Extension with accessibility to inputs to producers made possible by the NGO, SG2000 and 6), the participation of Guinean farmers in the testing and selection of the NERICAs and 7), the good performance of the NERICAs themselves.

3.2 Sampling and Data

This research is based on a survey data collected in 2001 from the four agro-ecological zones of Guinea where NERICA dissemination activities were being conducted. In each zone a further stratification was done into two types of *prefectures;* those where NERICA varieties had been introduced and those where NERICA varieties were not yet introduced. Within *prefectures* where NERICA varieties had been introduced (the NERICA *prefecture*), two villages where NERICA had been introduced were selected[11]. For each selected NERICA village, three or four neighbouring villages where NERICA had not yet been introduced by WARDA or IRAG were also selected[12]. A total of 79 villages were selected and a total of 1467 rice farmers were selected from the list of rice farmers in selected villages[13]. Data was collected at village and at farmer levels. At the village level, data collected included rice varieties grown and the village infrastructures. At the farmer level data collected included the farmer knowledge of varieties and varieties cultivated each year since 1997 and other socio-economic data. Prior to the survey a list of known modern and traditional varieties in the village was constructed and each farmer selected for the survey was asked whether he or she knew each of the varieties. If the answer to the question was a 'yes' then the farmer was asked whether he or she had cultivated the variety in the past five years (1997-2001).

[10] WAB450IBP28HB, WAB450IBP91HB and WAB450IBP160HB
[11] The selection of villages was not random as it purposely included villages where WARDA, IRAG or Sasakawa Global 2000 had introduced NERICA varieties through either on-farm trials or Participatory variety Selection (PVS).
[12] In anticipation of a study on biodiversity, two non-NERICA prefectures were also selected.
[13] The survey was restricted to rice farmers only

In the present study we define knowledge or exposure to a variety as a "yes" answer to the first question and adoption as the cultivation of the variety.

3.3 Characteristics of farmers

Table 1 reports descriptive statistics disaggregated by their adoption status for 1467 surveyed rice farmers. Over 90 % of the farmers were male, born in the same village they lived at the time of the survey. At the time of the survey, the average age of the farmers was 48 years. We observe that the family size is statistically different between adopters and non-adopters with adopters reporting larger household sizes. The education level of the household's head is significantly different between adopters and non adopters, with adopters reporting significantly more years of formal education than non-adopters. However, there are no significant differences in the attendance of professional training as well as in the type of experience in rice farming. We include in our set of characteristics a set of institutional characteristics, i.e., the percentage of farmers with access to credit, extension services and contact with WARDA and the NGO Sasakawa project. More NERICA adopters reported having access to extension services than non adopters. Also a higher proportion of NERICA adopters have contact with WARDA and the NGO Sasakawa.

Table 1: Household characteristics by adoption statuts

Characteristic	Non-adopters (n=1177)	Adopters (n=290)	Total (n=1467)	Difference
Socio-demographic factors				
Proportion of male farmers	93	97	94	3**
Proportion of female farmers	7	3	6	3
Age	48	49	48	-0.66
Household size	10	11	10	1**
% Born in the same village	90	93	90	2.4
Number of years of residence in the village	41	43	41	1.95*
Education and experience in rice farming				
Years of schooling	4.4	4.8	5	0.43**
Proportion of farmers reporting that they received professional training	12.5	13.8	13	2.2
Proportion of farmers with experience in low land rice farming	50	54	51	3.8
Proportion of farmers with experience in upland land rice farming	71	75	72	3.3
Proportion of farmers with experience in mangrove rice farming	6.8	7.9	7	7.0
Institutional factors				
Proportion of farmers in contact with WARDA	0.5	9	2	2.1***
Proportion of farmers in contact with SG2000	1.7	4.5	2	2.8***
Proportion farmers with access to credit	2.8	4	3	1

Proportion of farmers with access to extension	41	62	45	21***

Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

* Indicate that difference between adopters and non-adopters is statistically sifnficant at 95% level (t-tests are used for differences in means)

4 Results and discussions

4.1 Diffusion of NERICA rice varieties in Guinea

Table 2 shows in more detail the incidence of exposure and adoption of NERICA varieties among the sampled farmers. Both the exposure to and adoption of NERICA varieties increased between 1996 and 2001. Following dissemination efforts that begun in 1997 about 37 % of the sampled farmers reported that they were aware of at least one NERICA variety by 2001, an increase from 13 % in 1997. The upper Guinea recorded the highest proportion of farmers (66%) that were exposed to the NERICA varieties than lower Guinea (27%), forest Guinea (22%) and middle Guinea (42%). This can be explained by the fact that NERICA varieties that were being disseminated were upland NERICAs such that their dissemination might have also been concentrated in a zone that was more favourable for the cultivation of upland NERICA varieties.

Table 2: Evolution of NERICA Varieties Adoption: Proportion of farmers adopting

Characteristic	Lower Guinea (n=579)	Upper Guinea (n=358)	Forest Guinea (361)	Middle Guinea (169)	Total (1467)
Exposure to NERICA Varieties					
Proportion of farmers exposed to NERICA (%)					
1997	15	10	15	1	13
1998	16	24	17	1	17
1999	21	44	19	1	25
2000	26	62	21	24	34
2001	27	65	22	42	37
Adoption of NERICA Varieties					
Proportion of farmers who have adopted at least one NERICA (%)					
1997	10		13		8
1998	11	4	17		10
1999	13	17	17		14
2000	16	30	20	13	21
2001	16	30	19	16	20
Proportion among NERICA exposed farmers who have adopted at least one NERICA (%)					
1997	56		82		52
1998	58	15	93		52
1999	56	37	87		53
2000	57	46	92	41	57
2001	58	45	87	49	55

Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

The adoption trend of NERICA varieties is consistent with expectation and follows the same trend as the exposure to NERICA varieties. The proportion of farmers in the sample reporting that they cultivated at least one NERICA variety increased from 8% in 1997 to 20% in 2001. The adoption rates are highest in upper Guinea (30%) than in lower Guinea (16%) forest Guinea (19%) and middle Guinea (16%). There were more dissemination activities in the upper guinea that led to high exposure rates to the NERICA varieties because upper Guinea has a relatively favourable climate for the cultivation of short-cycle upland NERICA varieties which grow well in the upland. The low adoption rates in lower Guinea can be explained by the fact that most farmers there practice mangrove and freshwater plains rice farming systems. As stated earlier, these adoption rates are likely to be biased downwards because they include farmers who were not yet exposed to NERICA varieties and therefore they can not adopt unless exposed. In fact some farmers would have adopted the NERICA varieties if they had been exposed to them, but in this sample adoption rates they are considered as non adopters.

An assessment of adoption rates among the exposed sub-population appears more appealing because it some how addresses the problem of non-exposure bias. Results indicate that adoption rates among the farmers that were aware of NERICA varieties are much higher ranging from 52% in 1997 to 55% in the year 2001. An interesting observation is that although upper guinea registered a larger proportion of farmers that were aware of the NERICAs, the adoption rate among the exposed sub-sample is the lowest at (45%) followed by middle Guinea (49%). It was observed that the *prefecture* under study (Faranah) lies on the border with Sierra Leon. It appears that due to the civil war in Sierra Leon, in the 1990s till 2000, there were frequent border incursions by Revolutionary United Front combatants from Sierra Leone into the Franah *prefecture* which might have destabilized community activities, including the production of NERICA seed through Community Based Seed production System (CBSS). As for middle Guinea, the low adoption rates could be explained by its relatively unfavourable climatic conditions for rice cultivation and by the fact that farmers in the region traditionally grow more maize and other crops than rice. Pasal (2000) reports that middle Guinea produces the smallest proportion of rice (5%) compared against 33% for forest Guinea, 18% for upper Guinea and 10% for lower Guinea.

However, as observed by Diagne (2006) the adoption rates among the exposed farmers is likely to significantly over-estimate the population adoption rate due to the positive population selection bias by which the population most likely to adopt gets exposed first. Diagne (2006) points out that the positive selection bias arises from two sources. The first source is the farmer's self selection into exposure. The second source of selection bias is the fact that researchers and extension workers target their technologies at farmers that are more likely to adopt.

In the next sections we attempt to investigate the presence or not of exposure and selection bias in the sample estimated adoption rates through an application of econometric tools guided by the counterfactual outcomes framework discussed earlier and then we correct for the bias.

4.2 Determinants of Farmer's exposure to the NERICA varieties

Table 3 shows results from a probit estimation of the determinants of the probability of getting exposed to the NERICA varieties. Several variables show statistically significant coefficients at 5% level: education of the farmer, residence in a village that had hosted PVS activities or farm trials through which NERICA varieties were introduced (NERICA, village), residence in upper Guinea, residence in forest Guinea, experience in upland rice farming and the experience on low land rice farming. Other important factors include; being resident in a village where Sasakawa Global 2000 conducted agricultural activities, and residence in a village with a relatively higher number of known NERICA varieties.

Table 3: Probit estimates of the determinants of the of probability of exposure to the NERICA varieties

Variables	Estimated coefficients			Marginal effect		
	Coef.	Std. Err.		dy/dx	Std. Err.	
Year of schooling	0.04	0.01	**	0.01	0.00	**
Number of years resident in village	0.00	0.00		0.00	0.00	
NERICA village	0.32	0.09	***	0.09	0.03	***
Household size	0.01	0.01		0.00	0.00	
Female gender	-0.31	0.19		-0.08	0.05	
Middle Guinea	-0.17	0.15		-0.05	0.04	
Upper region	0.62	0.14	***	0.19	0.05	***
Forest region	-1.44	0.17	***	-0.32	0.03	***
Experience in upland rice farming	0.24	0.11	*	0.07	0.03	*
Experience in lowland rice farming	-0.31	0.10	**	-0.08	0.03	***
Village contact with SG2000	0.22	0.10	*	0.06	0.03	*
Total number of IRAG varieties known in village	0.01	0.02		0.00	0.01	
Total number NERICA varieties known in village	0.52	0.04	***	0.14	0.01	***
Total number traditional varieties known in village	0.00	0.00		0.00	0.00	
Extension	0.38	0.08	***	0.11	0.02	***
Constant	-1.80	0.23	***			
Number of interviews	1467					
LR Chi $\square^2$	479.49					
Pseudo R2	0.25					
Log of Likelihood	-715.832					

Key : * p<0.05; ** p<0.01; *** p<0.001

Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

Educated farmers are more likely to know NERICA varieties than those that are less educated. Farmers resident in a village with PVS activities (NERICA village) through which NERICA varieties were introduced are significantly more likely to know NERICA than farmer in villages where NERICA is not yet introduced. Farmers living in the upper Guinea region are significantly more likely to know NERICA than farmers in the lower Guinea and other regions. Diagne (2006) attributes this observation to the fact that the first-generation NERICA were bred for the upland ecology and their dissemination naturally concentrated in the upland areas such as in the upper Guinea where rain- fed upland rice farming is dominant. Farmers in the forest Guinea, are significantly less likely to know NERICA than those in the lower Guinea, which suggests that dissemination efforts concentrated more in other regions than in forest Guinea.

Experience in upland rice farming increases the likelihood of knowledge of NERICA while experience in low land rice farming reduces the probability of NERICA knowledge. Farmers living in a village where the NGO Sasakawa Global 2000 is active (SG2000 which plays an important role in agricultural extension and the supply of inputs) are significantly more likely to know NERICA. SG2000 is actively involved in facilitating the access to inputs and supplying credit to the rice farming community in Guinea. Farmers resident in the a village where farmers know a relatively larger number of NERICA rice varieties are significantly more likely to know NERICA. The probability of exposure to the NERICA is significantly high among farmers that have contact with an agricultural extension worker than among those that do not have access to extension services. These findings point to the urgent need to improve extension services in Guinea as a way to increase the awareness of NERICA among farmers

4.3 NERICA adoption rates and their Determinants

4.3.1 NERICA adoption rates

Table 4 presents the results of the estimation of the NERICA actual adoption rate (JEA) as estimated by the observed sample adoption rates and the population potential adoption rates (ATE) estimated using the two methods discussed above (IPW and ATE parametric). An important point to note is that the results are presented under two scenarios; thus with and without ATE correction for non-exposure and population selection biases discussed earlier. The results show that the population adoption rates under incomplete exposure – (joint exposure and adoption rate) is the same for the three different methods of estimation (IPW, ATE probit, and classic probit) estimated at (20%) and that they all yield the same range for the 95% confidence interval (between 18 % and 22 %). The finding that the sample estimate is the same as the estimate obtained by IPW and ATE probit methods suggests that the assumptions underlying the three models (eg, random sampling, distribution??) are plausible in as far as estimating the joint exposure and adoption rate for the whole population and its determinants is concerned (Diagne and Demont, 2007). The results further indicate that the joint exposure and adoption rate within the presently NERICA-exposed subpopulation estimated by the classical probit model (26%) is different from those estimated by the sample moments, ATE-Inverse propensity weighting and ATE-probit model (55%). Indeed it can be seen that the classic probit model estimate of 26% has a 95% confidence interval ranging between 25% and 27%, a range that is far below the consistently estimated value of 55%, a finding that suggests that the classic probit model has a problem of attenuation bias (Yatchew and Griliches, 1985) because the model is based on the full sample without controlling for exposure bias.

Diagne and Demont (2007) note that the downward bias of the classical probit model estimate of the probability of joint exposure and adoption for the NERICA-esposed subpopulation implies that its coefficient estimates are likely to be inconsistent for a model of determinants of adoption. These results, therefore, represent the expected joint exposure and adoption rate for the population which is not the desirable parameter of interest in most adoption studies.

Table 4 Estimates of NERICA adoption rates and their 95% confidence intervals [a]

Parameters	Sample moments estimate	Classical probit joint exposure and adoption model	Inverse probability weighting (IPW) estimator of ATE	ATE probit adoption model
Joint exposure and adoption rate (Probability of knowledge and adoption of at least one NERICA variety):				
In the full population	0.20 (0.18 0.22)	0.20 (0.19 0.20)	0.20 (0.18 0.22)	0.20 (0.18 0.22)
Within the NERICA-exposed subpopulation	0.55 (0.50 0.61)	0.26 (0.25 0.27)	0.55 (0.50 0.61)	0.55 (0.50 0.61)
NERICA adoption rate (Probability of adopting at least one NERICA variety):				
In the full population (ATE)			0.63 (050 0.76)***	0.61 (0.57 0.66)***
Within the NERICA-exposed subpopulation (ATE1)			0.55 (0.47 0.64)***	0.55 (0.52 0.59)***
Within the sub-population not exposed to the NERICAs (ATE0)			0.67 (0.48 0.87)***	0.64 (0.59 0.70)***
Estimated population adoption gap:				
Expected non-exposure bias(NEB)			-0.43 (-0.56 -.31)***	-0.41 (-0.45 -.38)***
Expected population selection bias (PSB)			-0.08 (-0.20 0.05)	-0.06 (-0.09 -.03)***

Key : * p<0.05; ** p<0.01; *** p<0.001

Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

The desirable parameter in adoption studies is the full population adoption rate (ATE) which provides an estimate of the potential demand of the NERICA technology by the target population. The full population adoption rate is estimated to be 63% by the ATE Inverse propensity weighting and 61% by the ATE probit method. This implies that the NERICA adoption rate in Guinea could have been 63% and 61% for the IPW and ATE probit model, respectively,, in 2001 if the whole population had been exposed to the NERICAs varieties, instead of the joint exposure and adoption rate of 20%. Thus when compared to the current sample adoption rate of 20%, there is a substantial population adoption gap due to the population's incomplete exposure to the NERICA varieties. The adoption gap is estimated at 43% and 41% for the IPW and ATE probit methods, respectively, with the two estimates being statistically significantly different from zero at 1% level. This finding implies that there is potential for increasing adoption rate by 43% or 41% once all farmers become aware of the NERICA varieties.

The adoption rate within a sub-population of farmers that are exposed to NERICA varieties (ATE1) is estimated to be 55% for both the IPW and the parametric probit model, while the estimated adoption rate within the sub-population not yet exposed to the NERICA varieties (ATE0) is 67% for the IPW method and 64% for the parametric probit model.

The estimated population selection bias (PSB) is 8% for the IPW model and 6% for the ATE probit model and they both are significantly different from zero. This implies that the adoption probability for a farmer belonging to the sub-population of informed farmers is significantly different from the adoption probability for any farmer within the population. The negative PSB indicates that the farmers exposed to the NERICA varieties are significantly less likely to adopt at least one NERICA variety than any farmer randomly selected from the population. Based on this observation, we reject the null hypothesis that a farmer selected randomly within a population has the same probability of adopting NERICA varieties as a farmer selected within the sub-population of those informed about NERICA varieties.

4.3.2 Determinants of NERICA adoption

Results on the determinants of NERICA adoption for the classic "adoption" model, the IPW model and ATE probit model are presented in Tables 5 and 6. There are striking differences in the magnitude of the coefficients as well as their marginal effects between the two models. In general the marginal effects of the ATE probit model are larger in absolute values than than of the classic "adoption" model. However, it is important to note that some coefficients are significant in both models while some are significant only in the ATE probit model. Results show that factors such as access to extension, the total number of IRAG varieties known by the farmer, and being resident in forest Guinea contribute positively to the probability of NERICA adoption in Guinea. Among these factors, residence in forest Guinea has the highest positive marginal contribution of 22% followed by the access to extension of 17%, and by the number IRAG varieties known by the farmer (9%).

The probability of NERICA adoption by a farmer diminishes with being a female farmer, being resident in middle and upper Guinea, and the total number of traditional varieties known by the farmer. Among factors with a negative contribution to the probability of adoption, being a female farmer is the most important with a negative marginal effect of 25%, followed by residence in upper Guinea (24%), residence in middle Guinea (18%) and the total number of traditional varieties (3%).

The negative correlation between adoption status and the gender of the farmer suggests that women are discriminated against when it comes to NERICA cultivation. This finding is consistent with an observation made by Lo (2000) in which it is observed that despite their role as the backbone of food production and provision for family consumption in the Sahel, women have limited access to critical resources, technology inputs and support services such as credit and extension due to cultural, traditional and sociological factors. The World Bank (1995) also note that rural women in the Sahel[14] are not frequently reached by extension services and are rarely members of co-operatives, which often distribute government subsidized inputs to small farmers.

Table 5: Classical and ATE corrected models of NERICA adoption: coefficients estimated

Variables	ATE probit adoption			Classic probit adoption model		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Age	0.00	0.01		0.00	0.00	
Year of schooling	0.02	0.02		0.03	0.01	
Number of years resident in village	0.01	0.00		0.00	0.00	
NERICA village	-0.09	0.15		0.18	0.09	
Household size	0.01	0.01		0.01	0.01	
Female gender	-0.85	0.33	*	-0.43	0.24	
Middle Guinea	-0.59	0.26	*	-0.03	0.16	
Upper Guinea	-0.81	0.22	***	0.17	0.15	
Forest Guinea	0.76	0.33	*	-0.19	0.19	
Experience in upland rice farming	-0.12	0.18		0.06	0.11	
Experience in lowland rice farming	-0.24	0.16		-0.18	0.10	
Extension	0.61	0.14	***	0.48	0.09	***
Total number of IRAG varieties known by farmer	0.31	0.05	***	0.10	0.05	*
Total number of traditional varieties known by farmer	-0.10	0.02	***	0.03	0.01	**
Village contact with SG2000				0.31	0.10	**
Total number of IRAG varieties known in the village				-0.02	0.04	
Total number of NERICA varieties known in the village				0.38	0.05	***
Total number of traditional varieties known in the village				-0.02	0.01	**
Constant	0.44	0.39		-2.03	0.25	***
Number of sample farmers	523			1467		
LR Chi χ^2	105.690			201.660		
Pseudo R2	0.181			0.157		
Log of Likelihood	-294.43			-614.82		

Key : * p<0.05; ** p<0.01; *** p<0.001
Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

Also consistent with this notion, in their analysis on the impact of gender discrimination on productivity and technical efficiency in Benin Kinkingninhoun-Mêdagbé et al (2008) observe that female rice farmers in Benin are particularly discriminated against with regards to the access to production resources resulting into significant negative impacts on their productivity and income.

The total number of traditional varieties known by the farmer significantly reduces the likelihood of NERICA adoption , an observation that can be attributed to the fact that the existence of numerous traditional varieties gives farmers such a wide range of choices hence reducing the probability of choosing NERICA varieties. The low probability of adoption associated with residence in the upper and middle Guinea can partly be attributed to the fact that other than NERICA, a variety of upland rice

[14] The study focused on Burkina Faso, Mali, Mauritania, Senegal and The Gambia

varieties were disseminated in the two regions such that this gave farmers a wider range of choices hence reducing the probability of choosing NERICA. However, as stated earlier due to the civil war in Sierra Leon in the 1990s till 2000, frequent border incursions by Revolutionary United Front combatants from Sierra Leone into the upper Guinea (specifically Franah *prefecture)* might have led to the disruption of NERICA seed production through Community Based Seed production System (CBSS), hence farmers could not access seed.

Table 6: Classical and ATE corrected models of NERICA adoption: marginal effect

Variable	ATE probit adoption			Classic probit adoption model		
	dy/dx	Std. Err.	P>z	dy/dx	Std. Err.	P>z
Age	0.00	0.00		0.00	0.00	
Years of Schooling	0.01	0.01		0.01	0.00	
Number of years resident in village	0.00	0.00		0.00	0.00	
NERICA village	-0.03	0.04		0.04	0.02	
Household size	0.00	0.00		0.00	0.00	
Female gender	-0.25	0.09	**	-0.09	0.04	*
Middle Guinea	-0.18	0.08	*	-0.01	0.04	
Upper Guinea	-0.24	0.07	***	0.04	0.04	
Forest Guinea	0.22	0.09	*	-0.04	0.04	
Experience in upland rice farming	-0.04	0.05		0.01	0.03	
Experience in lowland rice farming	-0.07	0.04		-0.04	0.02	
Extension	0.17	0.04	***	0.11	0.02	***
Total number of IRAG varieties known by farmer	0.09	0.01	***	0.02	0.01	*
Total number of traditional varieties known by farmer	-0.03	0.00	***	0.01	0.00	*
Village contact with SG2000				0.08	0.03	**
Total number of IRAG varieties known in village				0.00	0.01	
Total number NERICA varieties known in village				0.09	0.01	***
Total number traditional varieties known in village				0.004	0.00	*
Number of interviews	1467			1467		

Key : * p<0.05; ** p<0.01; *** p<0.001
Source: WARDA/IRAG/SNPRV 2004, NERICA Impact Study

The positive impact of access to extension services is consistent with prior expectation. Indeed extension plays an important role in the five stages of the adoption process proposed by Rogers (2003), namely (a) knowledge, (b) persuasion, (c) decision, (d) implementation, and (e) confirmation. The findings suggest that agricultural extension workers in Guinea have had a significant impact in creating awareness of the NERICA among farmers and in persuading them to adopt NERICA cultivation. However, in this study, only 45 percent of the farmers reported having access to extension advice which suggests that there is scope for increasing the cultivation of NERICA through an intensification of extension efforts.

The total number of IRAG varieties known by the farmer increases the probability of NERICA adoption because apart from disseminating other rice varieties, IRAG also participated in the dissemination of the NERICA varieties. Being resident in forest Guinea increases the probability of adoption because the region has favorable conditions for the cultivation of upland rain-fed NERICAs that were disseminated in Guinea.

5 Conclusions

This study has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. We find that NERICA adoption rates in Guinea could have been up to 61% in 2001 instead of the observed sample adoption rate of 20% if the whole population was exposed to the NERICA varieties by the year 2001. The non-exposure bias of 41% suggests that there is potential for increasing the NERICA adoption rate by 41% if its diffusion to the population can be completed. The success in the dissemination of NERICA in Guinea was a result of coordinated efforts by several stakeholders including farmers, donors, non-governmental organizations and the ministry of agriculture. The 37% NERICA exposure rate indicates that there is still potential for increasing the farmers awareness of the NERICAs through increased dissemination efforts. The study also shows that the exposure to NERICA and their adoption by farmers is influenced by a number of factors. Among others the probability of adopting at least one NERICA variety is high among farmers that have access to extension services, but it diminishes with being a female farmer and with knowledge of more traditional varieties.

This paper has provided estimates of actual and potential adoption rates and the determinants of adoption for the NERICA varieties in Guinea and has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. Three main conclusions are drawn from the study. First, there is potential for increasing the farmer's awareness of the NERICAs through increased dissemination efforts. The rate of NERICA awareness among the sampled farmers increased from 13% in 1997 to 37% in 2001. Related to this is the fact that the success in the dissemination of NERICA in Guinea was a result of coordinated efforts by several stakeholders including farmers, donors, (e.g, the World Bank), collaborative efforts put in place by different departments of the Guinean Ministry of Agriculture, the additional support to Research and Extension with accessibility to inputs to producers made possible by the NGO, SG2000, the participation of farmers in the testing and the selection of the NERICAs, and the superior performance of the NERICA varieties in terms of yield and other attributes. This emphasizes the importance of partnerships in successfully implementing dissemination activities.

Secondly, the study has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. The study has shown that there is potential for increasing the adoption rate of the NERICA varieties in Guinea. We find that NERICA adoption rates in Guinea could have been up to 61% in 2001 instead of the observed sample adoption rate of 20% if the whole population was exposed to the NERICA varieties by the year 2001.

These non-awareness bias of 41%, suggests that there is potential for increasing the adoption rate by 41% if the diffusion of the NERICA varieties to the population can be completed and therefore, this is a justification for a further investment in the dissemination of the NERICA varieties

Last, the study has shown that the exposure to NERICA and their adoption by farmers is influenced by a number of other factors. Apart from variety-characteristics (short-cycle, resistance to drought and weeds), several other factors explain the varying dissemination rates as well as adoption. The probability of a farmer's awareness of at least one NERICA variety is higher among the farmers with more years of formal schooling, farmers residing in villages where NERICA varieties have been introduced, those resident in a village with more known NERICA varieties, and among farmers with access to extension advice. The probability of cultivating at least one NERICA variety is high among farmers that have access to extension services, farmers with knowledge of more NERICA varieties, and farmers resident in a NERICA village and in forest Guinea. The probability of adoption diminishes with being a female farmer, knowledge of more traditional varieties, and being resident in the regions of upper and middle Guinea. These findings have implications for the emphasis on NERICA dissemination programs that could help in exposing households to the NERICA varieties. The presence of exposure bias suggests that there is scope for increasing the adoption of NERICA varieties by increasing the the awareness of NERICA among farmers. Supporting farmers, particularly, women with extension services would significantly increase their participation in NERICA cultivation.

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