Center of Evaluation for Global Action
Working Paper Series

Agriculture for Development
Paper No. AfD-0905
Issued in July 2009

# Technological Change in Smallholder Agriculture: Bridging the Adoption Gap by Understanding its Source.

Aliou Diagne

Africa Rice Center (WARDA)



Series Description: The CEGA AfD Working Paper series contains papers presented at the May 2009 Conference on "Agriculture for Development in Sub-Saharan Africa," sponsored jointly by the African Economic Research Consortium (AERC) and CEGA.

Recommended Citation: Aliou Diagne. (2009) Technological Change in Smallholder Agriculture: Bridging the Adoption Gap by Understanding its Source. CEGA Working Paper Series No. AfD-0905. Center of Evaluation for Global Action. University of California, Berkeley.

# Technological Change in Smallholder Agriculture: Bridging the Adoption Gap by Understanding its Source†‡

**Aliou Diagne***

This draft: May 2009

† Invited paper prepared for the AERC conference on Agriculture for Development, Session 2: Technological change in smallholder agriculture. Whitesands Hotel, Mombasa, Kenya May 28-29, 2009. The paper draws from joint collaborative work being conducted with the National Agricultural Systems of the member countries of the Africa Rice Center (WARDA)

‡**Acknowledgement:** My deep gratitude goes to the late Marie Jose Sogbossi who has assisted me magnificently in this work from 2005 until her untimely death last December. My gratitude goes also to my collaborators in the National Agricultural Systems without whom most of the work reported here would not have been possible. I would like also to thank especially Florent Kinkingninhoun-Mêdagbé and Gnona Midingoyi for excellent research assistance in the writing of this paper. My Thanks goes also to Perpetue Kouame and Simon Ncho for the assistance provided in the processing of the data and to my WARDA colleagues for useful discussions on the subject of the paper. The financial supports of the European Union, the Government of Japan, the United kingdom and the African Development Bank are gratefully acknowledged.

* Program Leader and Impact Assessment Economist, Policy and Impact Assessment Program, The Africa Rice Center (WARDA) B.P. 2031 Cotonou, Benin Tel: (229) 21 35 01 88 Fax: (229) 21 350 556. E-mail: A.Diagne@cgiar.org

**Technological Change in Smallholder Agriculture: Bridging the Adoption Gap by Understanding its Source**

## Abstract

This paper examines the informational origin of the low adoption rates of modern agricultural technologies frequently observed in smallholder agriculture in Sub-Sahran Africa. The paper argues that a large part of these observed low adoption rates can be explained by a simple fact: The lack of awareness of the existence of the technology by a large proportion of the smallholder farming population. The paper analyzes the structure of the *adoption gap* resulting from this lack of awareness and presents a methodology for estimating that gap and truly informative adoption rates and their determinants. This methodology is then used to provide estimates of the New Rice for Africa (NERICA) population potential adoption rates and gaps as well as estimates of the determinants of NERICA exposure and adoption in four West African Countries: Cote d'Ivoire, Guinea, Benin and Gambia.

The implied estimated adoption gaps of 21% in Cote-d'Ivoire, 41% in Guinea, 28% in Benin and 47% in Gambia suggest that there is potential for increasing NERICA adoption significantly in these four countries. The results of the analysis of the determinants of NERICA adoption highlight the importance of Participatory Varietal Selection (PVS) trials and farmer access to extension services in promoting the adoption of NERICAs beyond their beneficial effects in making farmers aware of the existence of the varieties. The findings also points to some possible gender biases in the dissemination of NERICA varieties in Guinea.

**JEL classification codes:** C13, O33, Q12, Q16

**Keywords:** Technology diffusion, Adoption, adoption gap, selection bias, Average Treatment Effect, NERICA.

**Technological Change in Smallholder Agriculture: Bridging the Adoption Gap by Understanding its Source**

## 1. Introduction

The vast majority of farmers in developing countries are smallholders, with an estimated 85 percent of them farming less than two hectares (World Bank, 2008). Hence, as emphasized in the 2008 World Development report, the potential of agriculture to contribute to growth and poverty reduction depends on the productivity of small farms. And, raising that productivity will require a much higher level of adoption of new agricultural practices and technologies than presently observed in the smallholder farming population (World Bank, 2008; De Janvry and Sadoulet, 2002). This paper examines the informational origin of the low adoption rates of modern agricultural technologies frequently observed in smallholder agriculture in Sub-Saharan Africa. The paper argues that a large part of these observed low adoption rates can be explained by a simple fact: The lack of awareness of the existence of the technology by a large proportion of the smallholder farming population. This is especially true when the technology is relatively new.

Before proceeding further, we need to clarify the meaning of the two concepts of diffusion and adoption as used in this paper. In most of the voluminous adoption literature, the two concepts of adoption and diffusion are used interchangeably. Often, in papers that make the distinction between the two concepts explicitly or implicitly, the adoption of a technology is defined at the individual level to mean its *use* while the concept of diffusion is defined at the aggregate population level to mean the *propagation* of *use* of the technology in the population (Sunding and Zilberman, 2001; Feder et al. 1985). In other words, the extent of adoption in the population.[1] Obviously, a technology must be known to someone before it can be used. But, no distinction is generally made in the common use of the two concepts between the mere knowledge or *awareness* of the existence of a technology (without necessarily using it) and its use. Such distinction is made in this paper. As in Diagne and Demont (2007) and Diagne (2006), The adoption of a technology is defined in this paper to mean its use at the individual level or at the aggregate population level. To be more precise, we will speak of adoption status or adoption intensity at the individual level and adoption rate at the aggregate population level. The term diffusion is used strictly in this paper to mean the extent of awareness of the technology in the population (which does not necessarily imply its use).[2]

If awareness of the existence of the technology by the population is not universal, the diffusion rate as commonly used must be understood as the rate of population awareness *and* adoption, which combines two different rates information: 1) the rate at which the population is being made aware of the technology, which we call the *diffusion* rate in this paper) and 2) the rate at which the part of the population which is aware of the technology is *using* it, which we call the *adoption rate among the exposed* in this paper.[3] The product of the diffusion rate and the adoption rate among the exposed is the *actual*

[1] There is often a time or space dimension embodied in the common use of the diffusion concept.
[2] The implicit assumption in the common definition and use of the concept of diffusion rate is that the population exposure to the technology is universal and only the number of individuals adopting (or disadopting) it changes through time. Hence, the significance of "diffusion rate" in this case is really the adoption rate conditional on universal exposure. This is what we call the population adoption rate (or potential adoption rate) in this paper.
[3] We will use the two terms of awareness and exposure interchangeably throughout the paper. However, our use of the term exposure in this paper is synonymous to awareness of the existence of the technology and does not necessarily imply any knowledge of the characteristics of the technology.

adoption rate that is consistently estimated by the proportion of adopters from a random sample of the population. As argued below, among all these quantities, only the population adoption rate is in general informative about the intrinsic merit of a technology in terms of the extent of its desirability by the target population. The difference between the population adoption rate and the actual adoption rate is what we call the population "non-exposure" bias, which exists solely because of the incomplete diffusion of the technology in the population. It measures in some sense the *unmet* population demand for the technology and will be, therefore, called simply the *adoption gap*. Thus, the title of the paper.

Despite, the fact that pioneers of adoption studies like Rogers (1983) and Beale and Bolen (1955, cited in DuberKow and McBride), have emphasized the critical importance of awareness in the adoption process, most empirical studies of adoption have either ignored the issue or have dealt with it inappropriately. In fact, except for few exceptions empirical adoption studies have so far neglected to collect information on the awareness status of farmers with respect to the technology being studied. The vast majority of agricultural technology adoption studies do emphasize the critical role that access to information plays in the adoption process (see Sunding and Zilberman, 2001 and Feder et al. 1985; for reviews of the literature) and empirical models of adoption usually includes some information related variables (notably access to extension services) to account for that fact (see, for example, Adesina and Baidu-Forson, 1995; Adesina and Zinnah 1993). However, most of the focus on the role of information in the adoption process has been on the type of information related to the characteristics and performance of the technology and the farmer's learning process leading to the acquisition of that information (Cameron 1999; Batz et al. 1999; Wozniak, 1993; Feder and Slade, 1984). But, having information about the characteristics and performance of a technology is conceptually and empirically different from merely being aware of the existence of the technology. Furthermore, awareness of the existence of a technology is sine qua non to its adoption (i.e. use) while, in principle, one can start using a new technology while knowing nothing about its characteristics or performance. It is this fact (i.e. the fact that awareness is prerequisite for adoption) that makes accounting for it fundamental in adoption studies, especially when the technology studied is relatively new. In particular, the usually computed sample adoption rate is uninformative with respect to the expected population adoption rate when only few farmers are aware of the existence of the new technology and one is interested in knowing to what extent the new technology satisfies the population's demand for new technologies. In fact, as shown in Diagne and Demont (2007) and Diagne (2006), the *observed* sample adoption rate is a consistent estimator of the combined rate of awareness and adoption. The confounding of the awareness and adoption information in the same rate makes it impossible to infer from the observed sample adoption rate the *potential* population adoption rate, which from a policy perspective, is the quantity that informs on the intrinsic value of the technology to society and the desired policy action. In particular, one cannot know whether a low observed sample adoption rate is caused by a very low population potential adoption rate or by just low awareness of the existence of the technology in the population. As pointed out by Diagne (2006), these two possible causes lead to contrasting policy implications: A high potential population adoption rate that is masked by a low level of awareness points to the need for more effort on extension to make the variety known and available to the larger population. On the other hand, if the potential population adoption rate is low, further extension effort to disseminate the variety may not be worth its cost.

Similarly, without accounting for the awareness status of farmers, empirical models of the determinants of adoption are not informative on the factors favoring or constraining adoption, except when awareness of the technology in the population is universal. In other words, one cannot consistently estimate the effects of the factors influencing adoption in such models. Indeed, such models are fundamentally unidentified, meaning essentially that the significations of the quantities they estimate (coefficient estimates and marginal effects) are different from what most think they are. The fundamental difficulty in interpreting the coefficients and marginal effects estimates out of classical model of the determinants of adoption has been pointed out by several authors including Dimara and Skuras (2003), Saha et. al., (1994), Besley and Case (1993) and Feder et. al, (1985). In fact, we will show in this paper that these coefficients and marginal effects estimates out of classical adoption models have indeed different meanings and that they can be very different from that arising from estimation of the "true" adoption function, which rightly and appropriately isolates the effect a factor has on adoption per se from its effect on the awareness status of a farmer. In particular, for the same data and same variables the marginal effects estimates from a classical adoption model can be 10 to 100 times smaller in magnitude compared to that from the rightly specified adoption model.[4] It goes without saying that such large difference in magnitude

[4] This empirical finding is understandable as one can show theoretically under some identifying assumption that the conditional mean "adoption" function estimated in the classical adoption model is equal to the true

and change in statistical significance will in most cases change qualitatively and in a significant way the conclusions one reaches from an adoption study.

The fact that awareness is a necessary condition for adoption has also important implications in terms of how the farmer awareness status information, when available, is accounted for in adoption models. Indeed, adoption model that does not properly handle the awareness status variable will quickly run into computational difficulties and will not produce results in most cases (i.e. the model estimation will end with an error message in most statistical software).[5] Or, if results are produced (with the aid of a specific functional form that artificially circumvents the problem), chances are that they will be grossly at odd with common sense and the basic facts because of the fundamental unidentifiability of the model. This is the case for example when the awareness variable enters additively in the observed adoption function directly or indirectly through a non-linear transformation.[6]

---

population average conditional adoption function (the "true" population adoption function) multiplied by the probability of being aware of the technology. Hence, for a factor determining adoption alone and not awareness, its marginal effect calculated from the classical "adoption" model is equal to its marginal effect from the true adoption model multiplied by the conditional probability of awareness, a quantity always between 0 and 1 and usually very small when not many farmers are aware of the technology. For a factor that is determinant of both adoption and awareness, the marginal effect calculated from the classical "adoption" model will be equal to the same product above plus a second term (made of the marginal effect with respect to awareness multiplied by the "true" population adoption function). This second term makes the comparison of the two marginal effects theoretically indeterminate. However, in practice the second term will be usually small for most factors in most data.

[5] This computational problem is well known in the Statistical literature.

[6] That is, the relation between awareness and adoption implies that it cannot be specified as $E(A \mid X = x, W = w) = g(\alpha W + \beta X)$ where $A$ is the observed adoption status variable, $W$ is the individual awareness status variable (equals to 1 if the individual is aware of the technology and 0 otherwise), $\alpha$ and $\beta$ are parameters and $g$ is a (possibly nonlinear) real valued function). This fact is overlooked by Daberkow and McBride (2003) in their empirical analysis of the influence of awareness on adoption. This alone can explain the "strange" results of their empirical model which made them conclude that awareness of precision agriculture technologies is not a determinant of their actual adoption. Daberkow and McBride tried to rationalize their findings but the conclusion reached is clearly in contradiction with the fact that awareness is a necessary condition for actual adoption.

The paper is organized as follows. Section 2 uses the finite population approach and a simple adopter/non-adopter type framework to illustrate and explain the "non-exposure" bias problem which is the source of the adoption gap when exposure to the technology is not universal. Section 3 uses the counterfactual outcomes and *average treatment effect* estimation framework to show how consistent non-parametric and parametric estimators of population adoption rates and their determinants can be obtained within this framework. Section 4 applies the results of section 3 to consistently estimate the population adoption rates and determinants of the NERICA (New Rice for Africa) rice varieties in Benin, Cote d'Ivoire, Gambia and Guinea along with estimates of the population "adoption gap" and selection biases created by the presently limited diffusion of the NERICAs. Section 5 concludes the paper with a summary of the major methodological and empirical results of the paper and their policy implications.

## 2. Anatomy of the source of the adoption gap: A finite population approach

To assess as simply as possible the magnitude of the adoption gap in commonly used sample adoption rate estimates, we use a finite population approach and focus on a population of farmers of size $N$, which can be divided into two groups based on a farmer's adoption attitude toward a given technology: an adopter-type group of farmers who will adopt the technology if exposed to it and an non-adopter-type group of farmers who will not adopt it if exposed to it (see Figure 1A). We assume that the type of a farmer is revealed only through exposure to the technology (see Figure 1B). In other words, one cannot know if a farmer is an adopter type or not, unless he or she is exposed to the technology. Let $N^a$ be the number of adopter-type farmers and $R^a = \frac{N^a}{N}$ be the proportion of adopter types in the total population. Hence, $R^a$ would be the true population adoption rate when exposure is complete in the population (i.e. when the entire population has been exposed to the technology).

**[Placement of Figure 1 about here]**

Now, suppose that the population is only *partially* exposed to the technology and let $N_e$ be the size of the exposed subpopulation and $R_e = \frac{N_e}{N}$ be the corresponding exposure rate. Let also $N_e^a$ be the number of adopters within the exposed sub-population and $N_0^a$ the number of adopter-type farmers in the non-exposed sub-population with $R_1^a = \frac{N_e^a}{N}$ and $R_0^a = \frac{N_0^a}{N}$ being the corresponding respective proportions in the total population and $R_e^a = \frac{N_e^a}{N_e}$ the proportion of adopters within the exposed subpopulation. Thus, the group of adopter-type farmers is further partitioned by the partial exposure into two sub-groups: one sub-group with farmers whose types are revealed and another subgroup whose types are still unknown (see Figure 1B). The group of non-adopters is also partitioned similarly.

It is important to note that the observable quantities in the above definitions are the total population size *N*, the size of the exposed subpopulation $N_e$ and the number of adopters in the exposed subpopulation $N_e^a$.[7] We cannot observe the total number of adopter types in the total population and in the non-exposed subpopulation $N^a$ and $N_0^a$,

[7] This observability assumes, of course, the feasibility of surveying the whole population.

respectively. So, we cannot compute the true population adoption rate $R^a$. We can only compute directly the proportion of *revealed* adopters in the population $R_1^a$, the exposure rate $R_e$ and the proportion of adopters within the exposed subpopulation $R_e^a$. However, since $N^a = N_e^a + N_0^a$, the knowledge of either $N^a$ or $N_0^a$ allow the computation of the other. The same applies for $R^a$ and $R_0^a$ because $R^a = R_1^a + R_0^a$. In the example illustrated in Figure 1, $N$=100, $N_e$ =20, and $N_e^a$=12 are observable. But, $N^a$= 40 and $N_0^a$=60 are not observable. Thus, the true population adoption rate $R^a$=40% and the proportion of non-exposed adopter-types in the population $R_0^a$=28% cannot be directly known.

With a random sample of farmers, the three observable population parameters ($R_1^a$, $R_e^a$ and $R_e$) are consistently estimated by their respective sample analogues (see Figure 1C).[8] In particular, the usually computed sample adoption rate (i.e. the proportion of sample farmers who have adopted) consistently estimates $R_1^a$ but not the true population adoption rate $R^a$ as commonly believed.

Given the definitions and notations above, we have:

$$\begin{aligned} R^a &= R_1^a + R_0^a = \frac{N_e^a}{N} + \frac{N_0^a}{N} = \frac{N_e}{N} \times \frac{N_e^a}{N_e} + \left(1 - \frac{N_e}{N}\right) \times \frac{N_0^a}{(N - N_e)} \quad \textbf{(1)} \\ &= R_e R_e^a + (1 - R_e) R_{0e}^a \end{aligned}$$

where $R_e^a$ and $R_{0e}^a$ are the adoption and would-be adoption rates within the exposed and non-exposed subpopulations, respectively.

[8] The zero-mean sampling error is ignored in the example for clarity.

The right hand side of the last equality of equation (1) shows that the true population adoption rate is the weighted average of $R_e^a$ and $R_{0e}^a$, the within exposed and non-exposed subpopulations adoption rates, respectively, with the weights given by the respective subpopulation shares.[9] But, more importantly, equation (1) shows that taking the sample analogue of $R_1^a$, the proportion of revealed adopters in a sample, as estimate of adoption rate generally leads to underestimation of the true population adoption rate $R^a$. As a measure of population adoption rate $R_1^a$ is incomplete in the sense that it does not take into account the would-be adopters whose types are not revealed. In the example illustrated in Figure 1, we have $R_1^a$ =12%, which understates the true population adoption rate (40%) by 28%.

We can see from equation (1) that the expected adoption gap or "non-exposure" bias, defined as **GAP**≡ $R_1^a - R^a = -(1 - R_e)R_{0e}^a$, is strictly negative and diminishing with increasing exposure rate. This shows that the incomplete population adoption rate $R_1^a$ always understates the true population adoption rate $R^a$, unless either the exposure rate is equal to 1 or the would-be adoption rate within the non-exposed subpopulation $R_{0e}^a$ is zero.

We can also obtain from equation (1) the expected bias resulting from using the sample analogue of $R_e^a$, the adoption rate within the exposed subpopulation, as estimate of the true population adoption rate $R^a$. This expected bias, which is caused by population selection into exposure, is given by **PSB** $\equiv R_e^a - R^a = (1 - R_e)(R_e^a - R_{0e}^a)$.

[9] It should be noted that normally both $R_e^a$ and $R_{0e}^a$ depend on the exposure rate $R_e$. But we are omitting showing this dependence to simplify the notation.

Because the population selection bias **PSB** can be either positive or negative depending on the relative magnitude of the two within subpopulation adoption rates $R_e^a$ and $R_{0e}^a$, $R_e^a$ can overestimate or underestimate $R^a$. Overestimation occurs when the adoption rate within the exposed subpopulation is greater than that of the non-exposed one. Otherwise we have underestimation. The population selection bias vanishes only when there is complete exposure or when the two within exposed and non-exposed subpopulation adoption rates are equal.

In the example illustrated in Figure 1, where the true population adoption rate is 40%, the relatively low population exposure rate of 20% leads to a population adoption gap of –28% and a positive population selection bias of +20%. The dependence of the population adoption gap and selection biases on the population exposure rate is illustrated in Figure 2 under positive (A), negative (B) and zero (C) population selection biases, respectively.[10]

**[Placement of Figure 2 about here]**

We can see from equation (1) and the preceding discussion that the sample proportion of revealed adopters is in fact an estimate of the population exposure *and* adoption rate. Indeed, $R_1^a$ is exactly the proportion of farmers in the total population who are exposed to the technology *and* who have adopted it. Therefore, such sample adoption

[10] In Figure 3 it is assumed that the deviation of the adoption rate within the exposed subpopulation from the true population adoption rate as a result of a population selection bias is a linear function of the exposure rate. That is, $\frac{\Delta R_e^a}{R^a} \equiv \frac{R_1^a - R^a}{R^a} = \alpha(1 - R_e)$, where α is the constant population selection bias parameter, with positive value indicating a positive population selection bias and a negative value the opposite. With this linear functional form assumption we have $R_e^a = (1+\alpha(1-R_e))R^a$ and $R_1^a = R_e R_e^a = (1+\alpha(1-R_e))R_e R^a$ (α=0.5 in Figure 2A and α=-0.5 in Figure 2B).

rate estimate embodies two types of information: information about the diffusion of a technology and that about its adoption. One would, however, argue that the question we are interested in an adoption study is the extent to which farmers *like* a given technology and not the extent to which they *know* about the technology. Indeed, it is the answer to the question of how liked is a technology that provides feedback to researchers regarding the suitability of their research product in terms of meeting the needs of the targeted population.   The answer to the question of how known is a technology is most useful for assessing the performance of extension systems or methods. By confounding the two different types of information, the sample proportion of revealed adopters provides little information on the population adoption rate when exposure is low.

We will see in the next section that within the treatment effect estimation framework the true population adoption rate $R^a$ is consistently estimated by the so-called *average treatment effect (ATE)*. As explained above, ATE measures the effect of applying a "*treatment*" to a randomly selected person in the population, whereas ATE1, the *average treatment effect on the treated*, measures the average effect of the treatment on the treated population. Hence, in our context, it is ATE1 that consistently estimates $R_e^a$, the adoption rate within the exposed subpopulation.

Before going into the estimation of ATE, however, one may want to have an answer to the following question of practical interest: if one cannot obtain the ATE estimate of the true population adoption rate $R^a$, which one between a consistent estimate of $R_1^a$ (the incomplete population adoption rate) and that of $R_e^a$ (the within exposed subpopulation adoption rate) to choose as a second best estimate of $R^a$? To answer this question, we will compare the absolute values of the population adoption gap (GAP) and selection bias (PSB) resulting from using $R_1^a$ and $R_e^a$ as an approximation of the true adoption rate of $R^a$. It is easy to see from the two bias formulas that $\mathbf{PSB} = \left(1 - \frac{R_e^a}{R_{0e}^a}\right) \times GAP$. Hence, $|GAP| < |\mathbf{PSB}|$ if and only if $R_e^a > 2R_{0e}^a$. In other words, the incomplete population adoption rate is a better approximation of the true adoption rate than the within exposed subpopulation adoption rate only when there is a strong positive population selection bias such that the within exposed subpopulation adoption rate is more than twice as large as the would-be adoption rate within the non-exposed subpopulation. Otherwise, the adoption rate within the exposed subpopulation is always a better approximation of the true adoption rate. In particular, the adoption rate within the exposed subpopulation is unambiguously better than the incomplete population adoption rate when there is a negative population selection bias such that the subpopulation least likely to adopt is exposed first (Figure 3B).[11]

In conclusion, although one cannot estimate the population selection bias through direct sample analogue computations to determine which situation one is faced with, one should always prefer $R_e^a$ to $R_1^a$ as a second best approximation of $R^a$, except when there are obvious indications that the exposed subpopulation is far more likely to adopt the technology compared to the non-exposed one.[12] In any case, instead of settling on a

[11] A negative population selection bias can occur, for example, in poverty targeted program that promotes a high yielding varietal technological package requiring use of fertilizer, which the targeted poor farmers cannot afford.

[12] This preference of $R_e^a$ over $R_1^a$ is further reinforced by the observation that when exposure is less than complete, **NEB** will be different from zero unless $R_{\bar{a}e}^a$ equals zero. In contrast, **PSB** can be equal to zero under less than complete exposure when $R_e^a$ and $R_{\bar{a}e}^a$ (the adoption rates within the two subpopulations of

second best population adoption rate estimate that may still carry a significant bias, one should really get the ATE estimate of $R^a$ when the additional data (covariates other than exposure and adoption outcomes variables) required for such estimation is available.

## 3. ATE estimation of population adoption rates and their determinants.

The *Average Treatment Effect* (ATE) methodology provides the appropriate framework for the identification and consistent estimation of population adoption rates and determinants (Diagne and Demont 2007; Diagne, 2006). 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 the technology, 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 technology 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 technology is a necessary condition for their adoption, we have $y_0 = 0$ for any farmer whether exposed to the technology or not. Hence, in this adoption context, ATE is reduced to the expected value $E(y_1)$ which is the population mean potential

---

exposed and non-exposed) are equal. This later event is arguably more likely to occur than that of $R^a_{\grave{a}e}$ equaling zero.

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), which we also call 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:[13] 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):

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

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\hat{p}(z_i)} \quad \textbf{(2)}$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n_e} y_i \quad \textbf{(3)}$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n}\frac{(1-\hat{p}(z_i))}{\hat{p}(z_i)}y_i \quad \textbf{(4)}$$

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. [14]

*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):

$$ATE(x) = \mathrm{E}(y_1 \mid x) = \mathrm{E}(y \mid x, w = 1) \quad \textbf{(5)}$$

[14] 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, 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 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*:

$$E(y \mid x, w=1) = g(x, \beta) \qquad \textbf{(6)}$$

where g is a known (possibly nonlinear) function of the vector of covariates *x* and the unknown parameter vector $\beta$ 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):

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

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta}) \qquad \textbf{(8)}$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta}) \qquad \textbf{(9)}$$

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:

$$\frac{\partial E(y_1 \mid \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k = 1,.., K \qquad \textbf{(10)}$$

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 ($G\hat{A}P = J\hat{E}A - A\hat{T}E$)[15], 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 $\Phi$ 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 technology and $\gamma$ 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.[16] 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

[15] 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: $J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} y_i$ .

[16] 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.

vector of covariates determining both exposure ($w$) and adoption ( $y_1$ ) and $\theta$ is the parameter vector to be estimated.[17] All the estimations were done in Stata using the Stata add-on *adoption* command developed by Diagne (2007) to automate the estimation of ATE adoption models and related statistical inference procedures.[18] 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

## 4. ATE estimation of NERICA diffusion and adoption rates and their determinants

The NERICA (New Rice for Africa) rice varieties, developed by WARDA in 1990s, are the result of interspecific crosses between *Oryza sativa* rice species from Asia and the locally adapted and multiple-stress resistant *Oryza glaberrima* African rice species.

[17] 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" 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.

[18] 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)

From 1996, NERICA were introduced in many African countries through Participatory Varietal Selection (PVS) trials and were then disseminated by farmers through their informal channels. In this section we estimate NERICA diffusion rates and its actual and population adoption rates and gaps in Cote d'Ivoire, Guinea, Gambia and Benin where they were introduced starting 1996 (Cote d'Ivoire and Guinea) and 1998 (Gambia and Benin). The determinants of NERICA diffusion and adoption in these four countries are also estimated.

### *Sampling and data*

The data used in the paper are collected from a sample of about 1,500 rice farmers in 50 villages in Cote d'Ivoire in 2000, 1467 rice farmers in 79 villages in Guinea in 2001, 360 rice farmers in 24 villages in Benin in 2004 and 600 rice farmers in 70 villages in Gambia in 2006. A Multi-stage stratified random sampling method was used to select the sample rice farmers in all four countries with the last two stages consisting of selecting the sample villages and farmers located in all the regions where NERICA has been introduced. The selection of sample villages was, however, not entirely random as it purposely included villages where WARDA has been conducting on-farm and participatory varietal selection (PVS) research activities. In selecting the sample villages, a list of all villages where NERICA seed were introduced (called NERICA villages) was constituted first. The sample NERICA villages were then randomly selected from that list. Then, for each sample NERICA village, a list of neighboring villages within 5 to 10 km where NERICA was not introduced (called non-NERICA villages) was constituted and 2 to 3 sample villages was randomly selected from that list. Thus, in Cote d'Ivoire

25 NERICA villages and 25 non NERICA villages were selected in the forest and savanna regions. In Benin, 12 NERICA villages and 12 non NERICA villages were selected in the central region. In Gambia, 35 NERICA villages and 35 non NERICA villages were selected in all the four agricultural regions of the country. In Guinea, the villages were selected among four agro-ecological zones where NERICA dissemination activities were being conducted. In each zone a further stratification was done into two types of Prefectures: NERICA Prefecture (where NERICA varieties had been introduced) and non NERICA prefectures (where NERICA varieties were not yet introduced). Within NERICA prefectures, two NERICA villages were selected and 3 to 4 non NERICA villages selected for each selected NERICA village for a total of 79 villages. Selection of farmers within the sample villages was done entirely randomly among the village population of rice farmers with the sample size varying across countries: 30 per village in Cote d'Ivoire, 15 per village in Benin, 20 per village in Guinea, and in Gambia, 10 form some region and 5 for other.

In each country, the data was collected at both village and farmer levels through a structured questionnaire. At the village level, the data collected included the rice varieties known in the village (modern and traditional) and village infrastructures and community variables. At the farmer level, the data included the rice varieties known and cultivated by the farmer and other socio-demographic data. Prior to administering the farmer level questionnaire, a list of the known varieties in the village was constructed from the village level survey and each sample farmer was asked his or her knowledge and cultivation of the varieties known in his or her own village.

*Demographic and socio-economic characteristics of sample farmers*

Table 1 reports selected descriptive statistics of the sample farmers in the 4 countries disaggregated by their adoption status. Common variables have been chosen[19] for the purpose of comparison and shortness. The Table shows that non adopters and adopters of NERICA in each country have approximately the same average of age in Cote-d'Ivoire where adopters seem to be older than non adopters, but the difference is not statistically significantly different from zero. The mean household size is higher in Gambia (16) than in the other countries (6 in Benin, 7 in Cote-d'Ivoire and 10 in Guinea). The differences in household size between adopters and non adopters are not statistically different from zero, however, except in the case of Guinea. The same pattern also shows for the education level of the household's head with adopters reporting significantly more years of formal education than non-adopters for Guinea. There are no significant differences between adopters and non-adopters across the four countries in the attendance of professional training as well as in the type of experience in rice farming.

**[Place of Table 1]**

The results in Table 1 show that women are the large majority of rice growers in Gambia (more than 90%) but they constitute a very small minority in Guinea (less than 5%). The proportion of female adopters in the sample is lower than female non-adopters, except in Cote d'Ivoire. The proportion of sample farmers with access to extension services is relatively high in Benin (more than 60%) and Guinea (more than 40%) compared to the other two countries. There are also more NERICA adopters with access to extension in

[19] Results including the non common variables are available upon request

these two countries compared to non-adopters whereas in Gambia and Cote-d'Ivoire the proportions of farmers with access to extension service is about the same for adopters and non adopters. As can be expected, in all four countries the proportion of NERICA adopters is higher in the NERICA villages compared to non-NERICA villages.

*Results of the ATE estimation of NERICA adoption rates and gaps*

The results of the estimation of the different NERICA diffusion and adoption rates and gaps are presented in Table 2. The NERICA diffusion rates are estimated to be 4% for Cote d'Ivoire in 2000, 39% for Guinea in 2001, 26% for Benin in 2004 and 57% in Gambia in 2006. Abstracting from country differences in NERICA dissemination efforts, we can see from these estimates a steady progress of NERICA diffusion from 2000 to 2006. Table 2 also shows that the estimation of the population joint exposure and adoption rates (JEA) using the two different ATE methods of estimation (Inverse Propensity Score Weighting estimator and ATE probit) yields the same estimates as the directly computed sample adoption rates for all the four countries and the estimates are statistically significant at 1% level. These joint exposure and adoption rates are 19% for Benin, 4% for Cote-d'Ivoire, 40% for Gambia and 20% for Guinea. The two methods also yield the same range for the 95% confidence interval (between 14% and 24% for Benin, 3% to 5% for Cote-d'ivoire, 36% to 43% for Gambia and 18% to 22% for Guinea). As demonstrated above, because of the relatively low diffusion of the NERICA varieties in all the four countries, these joint exposure and adoption rates estimates significantly understate the population adoption rate (i.e. the adoption rate that would obtain if the whole population were exposed to the NERICA varieties).

As shown in Table 2, the adoption rates within the NERICA-exposed subpopulation (ATE1) are estimated to be 52% for Benin, 37% for Cote-d'Ivoire, 86% for Gambia and 55% for Guinea with approximately the same range for the 95% confident intervals (respectively, between 39% to 65%, 27% to 48%, 77% to 94%, and 50% to 65%) for the two methods (IPSW and ATE Probit). The estimates are all statistically significant at the 1% level of significance. As explained above, these adoption rates among the NERICA-exposed sub population are likely to overstate the NERICA (potential) population adoption rates because of positive selection bias.

The NERICA population adoption rates (ATE), which inform on the demand of NERICA by the target population, is estimated to be 45%, 22%, 85% and 61% for Benin, Cote-d'Ivoire, Gambia and Guinea, respectively by the IPWS method and 47%, 24%, 87% and 61%, respectively by the ATE Probit model. The estimates are all statistically significantly different from zero at the 1% level of confidence. It can be seen that for each country, the ATE probit method shows in general adoption rates estimates that are 2 % higher than those of the IPSW method, except for the Guinea case where the two estimates are the same. We note also that the probability of adopting at least one NERICA varieties is the highest in Gambia, and the lowest in Cote-d'Ivoire.

The corresponding estimates of the NERICA population adoption *gap* (i.e non-exposure bias) as given by the IPSW and ATE Probit methods are respectively -26% and -0,28% in Benin, -19% and -21% in Cote-d'Ivoire, -45% and -47% in Gambia and -41% in Guinea, with all the estimates statistically significant at the 1% level. These adoption gap estimates imply that there is still potential for increasing NERICA adoption rates significantly in all the four countries. It should be emphasized that this adoption gap is solely due to the lack of awareness of the existence of NERICA. However, the size of the adoption gap depends on the same factors that determine the exposure and population adoption rates, the effects of which are estimated below. Hence, by appropriately changing the values of these determinants through some policy instruments, one can increase actual adoption through a simultaneous narrowing of the adoption gap and an increase in the population adoption rate.

The adoption rates within the subpopulation not exposed to the NERICA varieties (ATE0) are estimated by the IPSW and ATE Probit methods to be 41% and 44% in Benin, 21% and 23% in cote d'Ivoire, 84% and 88% in Gambia and 64% in Guinea. The estimated implied population selection bias (PBS) is 7% and 5% in Benin, 15% and 13% in Cote-d'Ivoire, -1% in Gambia and -5% and -6% in Guinea for the IPSW and ATE probit methods, respectively. The PSB estimates are all significantly different from zero at least at the 5% level for all countries in the case of the ATE probit model. This implies that the probability of adoption for a farmer belonging to the subpopulation of exposed farmers is significantly different from the probability of adoption for any other farmer randomly selected in the general population. The negative PSB for Guinea and Gambia 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.

*Determinants of NERICA exposure and adoption*

In this section we present and discuss the results of the estimation of the probit model of the determinants of exposure (i.e. awareness of) to the NERICA varieties and that of the determinants of NERICA adoption in the population from the parametric ATE probit model. The results of the estimation of the classic probit adoption model (which is in fact a model of the determinants of joint exposure and adoption as shown above) are also presented for comparison purposes. For ease of presentation, the results are presented in the tables country by country, although they are discussed together.

*Determinants of NERICA exposure*

Table 6, 7, 8 and 9 present the results of the exposure probit model and the marginal effects of the determinants of the probability of being exposed to the NERICA varieties in Cote d'Ivoire, Guinea, Benin and Gambia respectively. Several variables show statistically significant coefficients and marginal effects at the 5% level. Focusing on the marginal effects, the variables with significant marginal effects are for Cote d'Ivoire: living in a NERICA village (+43%), village contact with SATMACI/SODERIZ (the former extension agency, +7,5%), number of NERICA varieties known in the village (2%), number of traditional varieties known in the village (9%) and being from the Bete ethnic group (+25%). For Guinea, the main determinants of NERICA exposure are residence in a NERICA village (+11%), residence in upper Guinea (+19%), residence in forest Guinea (-28%), experience on lowland rice farming and (-11%), number of NERICA varieties known in the village and access toextension services (+10%). For Benin, only residence in a NERICA village and household size have significant marginal effects (32% and 3% respectively). In the case of Gambia, residence in a NERICA village and being located in the Western Region are the main determinants of the probability of being exposed to the NERICA varieties with positive marginal effects of 27% and 21%, respectively.

**[Place of Table 6, 7, 8 and 9]**

The results above show that across all 4 countries, living in a NERICA village (where the PVS activities were conducted) is the most important determinant of exposure to the NERICA varieties. Access to extension services are also important determinants of exposure for Cote d'Ivoire and Guinea. The results also show that rice farmers living in a village with relatively larger number of NERICA and traditional varieties are significantly more likely to be exposed to NERICA and that farmers who practice upland rice farming system are more likely to be exposed to the NERICA varieties, which is understandable given the fact that NERICA is an upland variety. It is notable that in Guinea women are less likely to be exposed to the NERICA varieties compared to men. This suggests that the dissemination activities may have been biased against women and that more targeting of women should be done. In Gambia, the fact that living in the Western Region was found to be an important determinant of exposure is not surprising because the first PVS activities were located in this region of the country (Tujereng and Jifanga villages). In addition, the fact that the headquarter of the National Agricultural Research Institute, NARI, is located in the same region can also explain the reason for the high probability of exposure to NERICA in the region.

*Determinants of NERICA adoption*

Table 10, 11, 12 and 13 present the results of the estimated coefficients and marginal effects of the ATE probit adoption model and the classical probit adoption model for Cote d'Ivoire, Guinea, Benin and Gambia. As explained above, one should keep in mind when interpreting the results that the classical "adoption" model is really a model of joint exposure and adoption. The results in the tables show in general marked differences in the magnitudes as well as statistical significances of the coefficients and the marginal effects between the two models. The differences are particularly striking for the cases of Cote d'Ivoire where the marginal effects of the ATE probit model are up to 100 times larger in absolute values than that of the classic "adoption" model.

The results show that factors such as living in NERICA village, past participation in PVS trials, being from the Bete or Senoufo ethnic group contribute positively to the probability of NERICA adoption in Cote d'Ivoire. Among these factors, living in a NERICA village has the highest marginal effect (+43%) followed by being from the Senoufo ethnic group (34%), being from the Bete ethnic group (25%) and past participation in PVS trials (21%). In Guinea, the results show that the factors that contribute positively and significantly to the probability of NERICA adoption are: being resident in forest Guinea (+21%), access to extension (17%), and the total number of IRAG varieties known by the farmer (9%), In the case of Benin, it is factors such as total land size and the age of the head of the household that contribute positively significantly to the probability of NERICA adoption in Benin (+12% and +6%, respectively) while for Gambia, it is only farmer contact with the Department of Agricultural services (DAS) that contributes positively to the probability of NERICA adoption in Gambia (9%).

**[Place of Table 10, 11, 12 and 13)]**

The results also reveal several factors that constraint NERICA adoption in the four countries. In Guinea, the probability of NERICA adoption diminishes with being a female farmer (-26%), living in upper Guinea (-25%), living in middle Guinea (-19%) and with the number of traditional varieties known by a farmer (-3%). In Benin, the probability of NERICA adoption diminishes with the squared of the age of the head of the household (-0.1%) while in the Gambia it diminishes with living in the North Bank Region (-21%) or in the Western Region (-19%) and with the nnumber of traditional varieties known by a farmer (2%).

We can draw some important conclusions regarding the major determinants of NERICA adoption across countries. First, one can see from the above findings the importance of the residence place of the farmer (NERICA village, in Cote d'Ivoire, being resident in forest Guinea for Guinea, and living in the Western Region or in the North Bank Region for Gambia) in affecting positively and significantly the probability of NERICA adoption in all the four countries, except in Benin. These residence places are often the villages or the regions where NERICA varieties have been introduced. However, it must be emphasized that these effects of the farmer's village and region of residence is on the probability of adoption per se and independently of the positive effect that the introduction of NERICA in those places has on the actual adoption (i.e. joint exposure and adoption) through increasing the probability of their awareness by farmers. These location specific effects reveal the importance of the conduct of PVS activities in those villages in increasing farmer knowledge of the characteristics of the NERICA varieties.

Indeed, farmers living in these areas, even if they are not participating in the PVS trials, can more easily visit the NERICA trials by themselves or discuss with PVS participants to learn about the varieties NERICA. This explanation is reinforced by the finding that direct participation in PVS trials has a significant and positive effect on NERICA adoption in Cote d'Ivoire. These location specific effects also reveal the suitability of the NERICA varieties to those identified regions relative to the others; an information very useful for targeting purposes in dissemination activities.

Second, the results also show the importance of access to extension services in determining NERICA adoption. The positive contribution of access to extension services is consistent with prior expectations and the general findings in the literatures (Sunding and Zilberman, 2001; Feder et al. 1985). This is also consistent with the role of extension as an importance source of information about the characteristics and performances of varieties for farmers and the importance such information plays in the five stages of the adoption process proposed by Rogers (2003): (a) knowledge, (b) persuasion, (c) decision, (d) implementation, and (e) confirmation. However, the results of the study show that the number of farmers who have access to extension advice remains relatively low in these countries which suggests that there is scope for increasing the cultivation of NERICA through an intensification of extension efforts. This is particularly important for Guinea and Gambia where agricultural extension workers have had a significant impact in persuading farmers to adopt the NERICA varieties in addition to creating awareness of them among farmers.

Third, the negative correlation between being female and NERICA adoption found in Guinea points to some possible gender biases in the way the NERICA varieties disseminated in Guinea were selected and introduced in the farming communities in Guinea. First, it is well known that the various NERICA lines tested in the PVS and on farm trials in Guinea differed on some key characteristics that are of importance to women (ease of threshing for example). It may well be that the NERICA lines that were ultimately selected for release and seed multiplication were the ones that satisfied mostly the varietal characteristics preferences of Guinean men rice farmers (high potential yield for example). Second, related to this point, Guinean extension workers, most of them men, may have focused their extension efforts on male farmers to the point that not much information on the differing characteristics and performances of NERICA varieties promoted in Guinea were provided to women. This finding is consistent with an observation made by Lo (2000) in which it is observed that despite their role as the backbone of the farm household's food production and 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 are not frequently reached by extension services and are rarely members of cooperatives, which often distribute government subsidized inputs to small farmers. Still, consistent with this notion Kinkingninhoun-Mêdagbé et al (2008), in their analysis on the impact of gender discrimination on productivity and technical efficiency in Benin, 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.

## 5. Conclusion

This study has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a new technology and its determinants. The paper has argued that the main source of the commonly observed low level of adoption of modern technologies in smallholder farming in Sub-Saharan Africa is lack of awareness of the existence of the technologies by smallholder farmers. The structure of the adoption gap resulting from this lack of awareness was analyzed in the paper and a methodology for estimating that gap and truly informative adoption rates and their determinants based on the ATE framework was presented and discussed. This methodology was then used to provide estimates of the NERICA population potential adoption rates and gaps as well as estimates of the determinants of NERICA exposure and adoption in four West African Countries: Cote d'Ivoire, Guinea, Benin and Gambia.

From a methodological point of views, four major conclusions can be drawn from the analysis of the paper with respect to the conduct of adoption studies. First, from a data collection point of view, adoption surveys must collect information on the farmer awareness of the existence the technologies. Otherwise, they are unlikely to lead to reliable estimates of adoption rates and their determinants. Second, when the diffusion of a technology in the population is not complete, estimated adoption rates from direct sample computation and from the classical adoption model are implicitly about joint exposure and adoption and do not inform about adoption per se. Third, it is the population adoption rate estimated through the ATE estimation framework that provides reliable information on the adoption of a technology in terms of its desirability and potential demand by the target population. Fourth, the difference between the observed joint exposure and adoption rate and the population adoption rate estimated through the ATE framework is the adoption gap that results from the lack of awareness of the existence of the technology, which we argue is the main cause of the observed low adoption rates of modern agricultural technologies in smallholder agriculture.

The results of the analyses of the determinants of NERICA exposure and adoption in Cote d'Ivoire, Guinea, Benin and Gambia show that, were the whole rice farming population of these four countries exposed to the NERICA varieties at the time of the surveys, their adoption rates could have been up to 61%, 24%, 47% and 87%, respectively instead of the estimated observed actual adoption rates of 4%, 20%, 19% and 40% for Cote d'Ivoire in 2000, Guinea in 2001, Benin in 2004 and for Gambia in 2006. The implied estimated adoption gaps of 21% in Cote-d'Ivoire, 41% in Guinea, 28% in Benin and 47% in Gambia suggest that there is potential for increasing the NERICA adoption significantly in these four countries.

The results of the analysis of the determinants of NERICA adoption illustrate the importance of controlling appropriately for awareness in adoption models. Three main empirical findings emerge from that analysis. First, the mere conduct of PVS trials in a village promote the adoption of NERICA beyond the subpopulation participating in the trials; most likely because it enables non-participating farmers to learn about the characteristics and performance of varieties from the participating farmers. This beneficial effect on adoption is in addition to the positive effect it has on actual adoption through increased awareness of the existence of the varieties among farmers.

Second, the importance of farmer access to extension services in promoting NERICA adoption was also a very important finding of the study. Like the PVS trials, access to extension services enables farmers to learn the characteristics and relative performances of varieties after they are made aware of their existence. This is consistent with the argument by Feder *et al*. (1985) and numerous other authors who emphasize the critical importance of this knowledge in farmer adoption decisions. According to Rogers (2003), knowledge of a new technology begins with information about its existence and understanding how it works. And, when the farmeris not involved in the development process of a new technology from the start, all adoption or rejection decisions are very much conditioned by his or her understanding of how it works.

Finally, the results of the analysis of the determinants of NERICA adoption in Guinea reveal a possible gender bias in the dissemination of NERICA varieties in that country. This is an important finding that requires a closer look of 1) the suitability of the NERICA varieties disseminated in Guinea to the particular needs of women rice producers and 2) the gender composition of extension service in Guinea and the way male extension agents work in rice farming communities.

## References

Batz, J.; Peters, K and Janssen, W. (1999). The influence of technology characteristics on the rate and speed of adoption. Agricultural Economics. 1999. 21 (2). 121-130

Beale, G and Bolen, J. 1955. How Farm People Accept New Ideas, Cooperative Extension Report No. 15, Iowa State University, Ames IA, USA.

Besley, Timothy and Anne Case (1993) "Modeling Technology Adoption in Developing Countries" *The American Economic Review*, Vol. 83, No. 2, Papers and Proceedings of the 105 Annual Meeting of the American Economic Association, Anaheim, California. pp. 396-402.

Cameron, L. (1999): The Importance of Learning in the Adoption of High-Yielding Variety Seeds, American Journal of Agricultural economics 81(1) 83-94

Daberkow and McBride (2003) Farm and operators characteristics affecting the awareness and adoption of precision agricultural technologies in USA. Economic research service, US Department of Agriculture. Washington DC 20036

Dalton, Timothy. J. (2004). "A household hedonic model of rice traits: economic values from farmers in West Africa." Agricultural Economics 31: 149 - 159.

De Janvry A and Sadoulet E.2002 World poverty and the role of agricultural technology: direct and indirect effects. Journal of Development Studies 38:4,1 – 26.

Diagne, Aliou. 2006. "The Diffusion and Adoption of NERICA rice varieties in Cote d'Ivoire". *The Developing Economies, Volume 44:2 June 2006*

Diagne, A. and M. Demont. (2007). Taking a New look at Empirical Models of Adoption:Average Treatment Effect estimation of Adoption rate and its Determinants. Agricultural Economics, Vol 37 (2007). 30p.

Dimara, E. and D. Skuras, 2003. "Adoption of agricultural innovations as a two-stage partial observability process". *Agricultural Economics*. 28: 187-196.

Doss, C. R., 2006. Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. Agricultural Economics 34(3):207-219.

Feder, G., R.E. Just and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey" *Economic Development and Cultural Change* 33 (2): :255-295.

Heckman, J. and E. Vytlacil, 2007. "Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy" in Handbook of

Econometrics, Vol. 6b, ed. by J. Heckman and E. Leamer. Amsterdam: Elsevier Science.

Heckman J and Vytlacil E. 2005, Structural Equations, Treatment Effects, and Econometric Policy Evaluation. *Econometrica* 73: 669-738.

Imben, G.W. 2004, "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review", The Review of Economics and Statistics, Vol. 86, Issue 1 pages 4-29..

Imbens, Guido and Jeffrey M. Wooldridge, 2009. "Recent Developments in the Econometrics of Program Evaluation," Journal of Economic Literature, 47:1, 5–86.

Kinkingninhoun-Mêdagbé, F, M., Diagne, A, Simtowe, F, Agboh-Noameshie, A, R. and P, Y, Adégbola 2008. Gender inequality and its impact on income, productivity and technical efficiency: Evidence from Benin. Agriculture and Human Values. 460-008-9170-9

Lee, Myoung_Jae. 2005 *Micro-Econometrics for Policy, Program and Treatment Effects.* Advanced Texts in Econometrics. Oxford University Press, New York.

Rogers, E.1983, "Diffusion of innovations", Third edition, The Free Press. New York.

Rosenbaum, P.R., and D. R.Rubin (1983), "The Central Role of the Propensity Score in Observational Studies for Causal Effects," Bometrika 70, 41-55.

Saha, L., L. H. Alan and S. Robert. 1994. "Adoption of emerging technologies under output uncertainty". *American Journal of Agricultural Economics*. 76: 836-846.

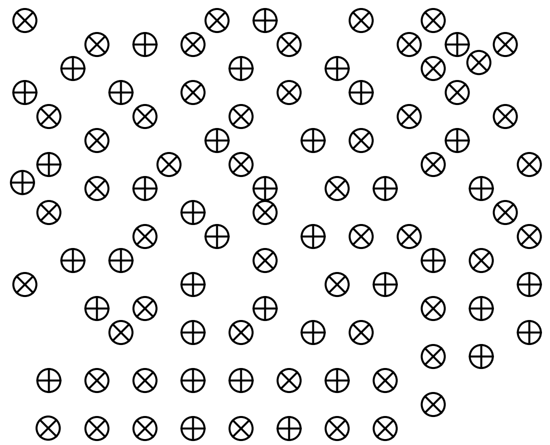
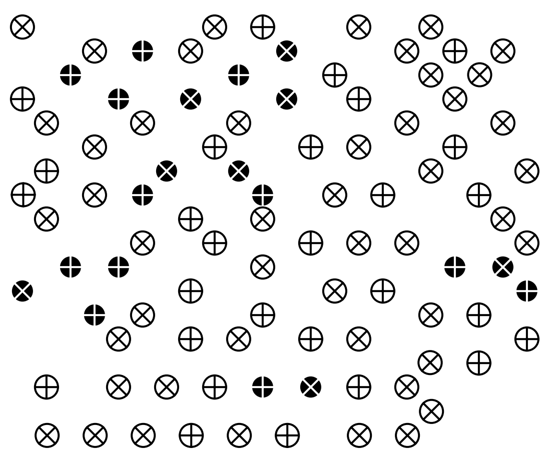
Sunding, D. and D. Zilberman. (2001) "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector." In: Bruce Gardner and Gordon Rausser (eds.), Handbook of Agricultural and Resource Economics. Elsevier Science, Amsterdam: North Holland. pp. 207-261.

Wooldridge, J. 2002, *Econometric Analysis of cross section and Panael data*. The MIT press, Cambridge, Massachusetts, USA.

World Bank (1995): Rural Women in the Sahel and their Access to Agricultural Extension . Sector Study: Overview of Five Country Studies. , http://www.worldbank.org/gender/know/eswafr.htm

Wozniak, G. D. (1993), Joint information acquisition and new technology adoption: Late versus early adoption, Review of Economics and Statistics 75(3), 438-45.

**Figure 1: Population adoption and Joint exposure *and* adoption rates under partial exposure to a technology and positive population selection bias**

| | | |
|---|---|---|
| **A**<br>Population before exposure<br>⊕ adopter type ⊗ non-adopter type |  | Total population size: $N$ = **100**<br>Adopter type sub-population size: $N^a$ = **40**<br>Non-adopter type sub-population size: $N_0^a$ =**60**<br><br>Expected population adoption rate:<br>$R^a = \frac{N^a}{N}$ = **40%** |
| **B**<br>Population after partial exposure<br>● exposed type ○ non-exposed type |  | Exposed subpopulation size: $N_e$ = **20**<br>Number of adopters among the exposed: $N_e^a$ = **12**<br>Non-exposed subpopulation size: $N - N_e$ =**80**<br>Number of adopter type among the non-exposed: $N_0^a$ =**28**<br>Population exposure *and* adoption rate: $R_1^a$ =**12%**<br>Population exposure rate: $R_e$ = **20%**<br>Adoption rate among the exposed: $R_e^a$ = **60%**<br>Adoption rate among the non-exposed: $R_{0e}^a$ =**35%**<br>Non-exposure bias: **NEB= -28%**<br>Population selection bias: **PSB=+20%** |

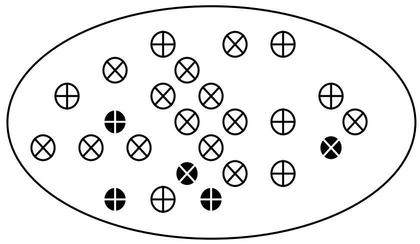
| | | |
|---|---|---|
| **C**<br>Random sample from the partially exposed population |  | Sample size: $n$ =**25**<br>Sample number of exposed: $n_e$=**5**<br>Sample number of (*revealed*) adopters: $n_a$ =**3**<br>Sample adoption rate: $\frac{n_a}{n}$ = **12%**<br>Sample exposure rate: $\frac{n_e}{n}$ =**20%**<br>Sample adoption rate among the exposed: $\frac{n_a}{n_e}$ = **60%** |

**Figure 2: Population adoption rates and non-exposure and selection biases as function of exposure rate**

**Figure 2A: The positive population selection bias case: the subpopulation most likely to adopt is exposed first**

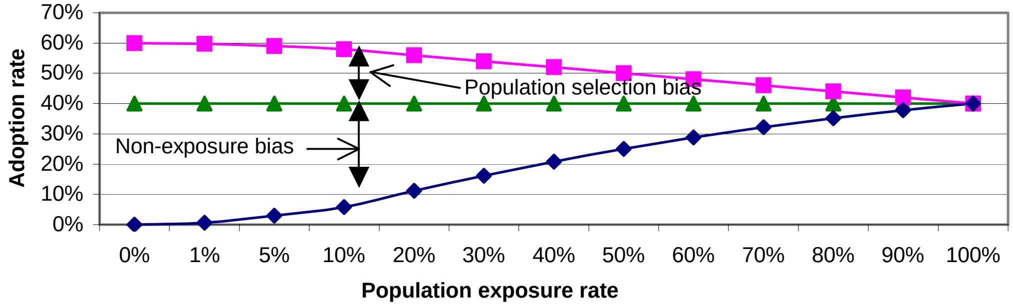



**Figure 2B: The negative population selection bias case: the subpopulation least likely to adopt is exposed first**

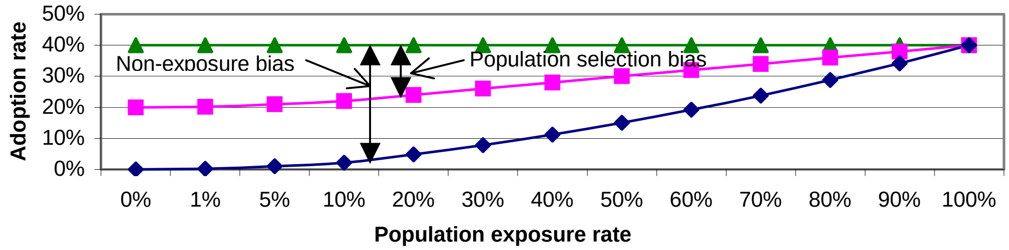
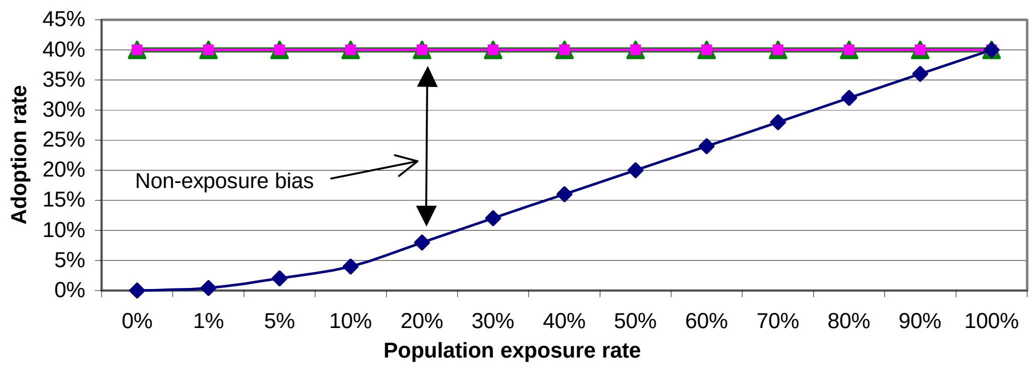
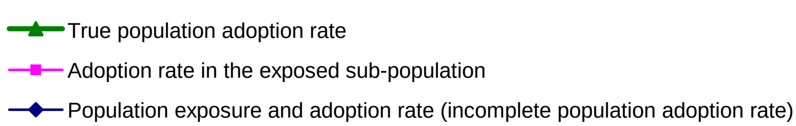



**Figure 2C: The zero population selection bias case: all subpopulation members are equally likely to be exposed**



## List of tables

Table1: Demographic and socio-economic characteristic of adopters and non-adopters.

| Characteristics | Benin | | | Cote d'ivoire | | | Gambia | | | Guinea | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Adoption | Non-adoption | Difference | Adoption | Non-adoption | Difference | Adoption | Non-adoption | Difference | Adoption | Non-adoption | Difference |
| Age | 42.98 | 42.72 | 0.015 | 43.774 | 40.898 | 0.147 | 45.186 | 45.129 | 0.003 | 48.717 | 48.049 | 0.035 |
| Household size | 7.24 | 5.71 | 0.383*** | 7.666 | 6.909 | 0.100 | 16.536 | 15.937 | 0.032 | 10.907 | 9.899 | 0.122** |
| Years of schooling | | | | 2.981 | 2.231 | 0.148 | 4.198 | 3.824 | 0.086 | 4.4 | 4.8 | 0.077* |
| Percentage of women | 58 | 61 | -3 | 43 | 34 | 9 | 92 | 94 | -2 | 3 | 7 | -4 |
| Percentage of men | 42 | 39 | 3 | 57 | 66 | -9 | 08 | 6 | 2 | 97 | 93 | 4 |
| Extension | 70 | 60 | 10 | 9.4 | 9.8 | -0.4 | 14 | 14 | 0 | 62 | 40 | 22 |
| Alphabetization | 8 | 5 | 3 | | | | 33 | 37 | -4 | 1.4 | 1.7 | -0.3 |
| NERICA village | 74 | 44 | 30 | 68 | 52 | 16 | 68 | 38 | 30 | 58 | 38 | 20 |
| Non-NERICA Village | 26 | 56 | -30 | 32 | 48 | -16 | 32 | 62 | -30 | 42 | 62 | -20 |

**Table 2: Estimates of NERICA Adoption rates in Cote-d'Ivoire and their 95% confidence intervals**

| Parameters | Sample moment estimates | Inverse propensity score weighting (IPW) estimator of ATE | ATE probit adoption model |
|---|---|---|---|
| NERICA exposure rate | 0.09 (0.08) | | |
| Joint exposure and adoption rate (Probability of knowledge and adoption of at least one NERICA variety): | | | |
| In the full population | 0.04 (0.005) | 0.04 (0.03 0.05) | 0.04 (0.03 0.05) |
| Within the NERICA-exposed subpopulation | | 0.37 (0.27 0.48) | 0.37 (0.27 0.48) |
| NERICA adoption rate ( Probability of adopting at least one NERICA variety): | | | |
| In the full population (ATE) | | 0.22 (0.10 0.35)*** | 0.24 (0.15 0.34)*** |
| Within the NERICA-exposed subpopulation (ATE1) | | 0.37 (0.27 0.47)*** | 0.38 (0.30 0.45)*** |
| Within the sub-population not exposed to the NERICA (ATE0) | | 0.21 (0.07 0.34)*** | 0.23 (0.13 0.33)*** |
| Estimated population adoption gap: | | | |
| Expected non-exposure bias(NEB) | | -0.19 (-0.31 -0.07)*** | -0.21 (-0.30 -0.12)*** |
| Expected population selection bias (PSB) | | 0.15 (0.03 0.26) ** | 0.13 (0.04 0.22) *** |

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

Table 3**:** Estimates of NERICA adoption rates in Guinea and their 95% confidence intervals

| | Sample moment estimates | Inverse propensity score weighting (IPW) estimator of ATE | ATE probit adoption model |
|---|---|---|---|
| NERICA exposure rate | 0.39 (0.08) | | |
| Joint exposure and adoption rate (Probability of knowledge and adoption of at least one NERICA variety): | | | |
| In the full population | 0.20 (0.04) | 0.20 (0.18 0.22) | 0.20 (0.18 0.22) |

| | | | |
|---|---|---|---|
| Within the NERICA-exposed subpopulation | | 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) | | 0.61 (0.50 0.71)*** | 0.61 (0.56 0.65)*** |
| Within the NERICA-exposed subpopulation (ATE1) | | 0.55 (0.47 0.64)*** | 0.55 (0.51 0.59)*** |
| Within the sub-population not exposed to the NERICA (ATE0) | | 0.64 (0.50 0.78)*** | 0.64 (0.59 0.70)*** |
| Estimated population adoption gap: | | | |
| Expected non-exposure bias(NEB) | | -0.41 (-0.50 -0.32)*** | -0.41 (-0.45 -0.38)*** |
| Expected population selection bias (PSB) | | -0.05 (-0.14 0.04) | -0.06 (-0.09 -0.03) *** |

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

Table 4: Estimates of NERICA Adoption rates in Benin and their 95% confidence intervals

| Parameters | Sample moment estimates | Inverse propensity score weighting (IPSW) estimator of ATE | ATE probit adoption model |
|---|---|---|---|
| NERICA exposure rate | 0.26 (0.07) | | |
| Joint exposure and adoption rate (Probability of knowledge and adoption of at least one NERICA variety): | | | |
| In the full population | 0.18 (0.06) | 0.19 (0.14 0.24) *** | 0.19 (0.14 0.24) *** |
| Within the NERICA-exposed subpopulation | | 0.52 (0.39 0.65) *** | 0.52 (0.43 0.61) *** |
| NERICA adoption rate ( Probability of adopting at least one NERICA variety): | | | |
| In the full population (ATE) | | 0.45 (0.33 0.56)*** | 0.47 (0.37 0.57)*** |
| Within the NERICA-exposed subpopulation (ATE1) | | 0.52 (0.35 0.69)*** | 0.52 (0.43 0.61)*** |
| Within the sub-population not exposed to the NERICA (ATE0) | | 0.41 (0.29 0.52)*** | 0.44 (0.32 0.56)*** |
| Estimated population adoption gap: | | | |
| Expected non-exposure bias(NEB) | | -0.26 (-0.33 -0.19)*** | -0.28 (-0.36 -0.20)*** |
| Expected population selection bias (PSB) | | 0.07(-0.02 0.17) | 0.05(-0.01 0.11)** |

Legend: * p<0.05; ** p<0.01; *** p<0.001
Source: WARDA

Table 5: Estimates of NERICA Adoption rates in Gambia and their 95% confidence intervals

| Parameters | Sample moment estimates | Inverse propensity score weighting (IPW) estimator of ATE | ATE probit adoption model |
|---|---|---|---|
| NERICA exposure rate | 0.57 (0.12) | | |
| Joint exposure and adoption rate (Probability of knowledge and adoption of at least one NERICA variety): | | | |
| In the full population | 0.40 (0.03) | 0.40 (0.36 0.43) *** | 0.40 (0.36 0.43) *** |
| Within the NERICA-exposed subpopulation | | 0.86 (0.77 0.94) *** | 0.86 (0.77 0.94) *** |
| NERICA adoption rate ( Probability of adopting at least one NERICA variety): | | | |
| In the full population (ATE) | | 0.85(0.75 0.95)*** | 0.87 (0.83 0.91) *** |
| Within the NERICA-exposed subpopulation (ATE1) | | 0.86 (0.70 1.02)*** | 0.86 (0.81 0.90)*** |
| Within the sub-population not exposed to the NERICA (ATE0) | | 0.84 (0.75 0.92)*** | 0.88 (0.84 0.92)*** |
| Estimated population adoption gap: | | | |
| Expected non-exposure bias(NEB) | | -0.45 (-0.50 -0.41)*** | -0.47 (-0.50 -0.45)*** |
| Expected population selection bias (PSB) | | -0.01(-0.08 0.10) | -0.01 (-0.02 -0.00)** |

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

**Table 6: Exposure probit model and marginal effects in Cote d'Ivoire**

| **Variable** | **Exposure probit model** | **Marginal effect (dy/dx)** |
|---|---|---|
| NERICA village | 0.92*** | 0.427*** |
| Village contact with ANADER | -0.20 | |
| Village contact with CIDT/GVC | -0.21 | |
| Village contact with SATMACI/SODERIZ | 1.57*** | 0.075*** |
| Number of NERICA varieties known in the village | 0.51*** | 0.023*** |
| Number of traditional varieties known in | 0.043*** | 0.002*** |

| | | |
|---|---|---|
| the village | | |
| Number of NARS upland rice varieties known in the village | -0.13* | -0.006* |
| Number of WARDA upland interspecific rice varieties known in the village | 0.07 | |
| Past participation to PVS trials | 0.10 | 0.210* |
| Practice upland rice cultivation | 0.89*** | 0.090 |
| lx5totar | 0.16 | -0.030 |
| Household size in 1996 | 0.01 | |
| Being born in the same village | 0.24 | |
| age | 0.003 | 0.000 |
| Having a secondary activity | 0.280* | 0.090 |
| Years of formal schooling | 0.039* | -0.010 |
| Being woman | 0.29 | 0.000 |
| Being from Ethnie Bete | -0.99*** | 0.249* |
| Being from Ethnie senoufo | 1.20 | 0.340** |
| Being in Forest zone | 0.91 | |
| Farmer contact with CIDT/GVC | | 0.220 |
| Farmer contact with SATMACI/SODERIZ | | 0.040 |
| Average Household size for the 5 past years | | 0.010 |
| _Constant | -6.19*** | |
| N | 1261 | |
| r2_p | 0.37 | |
| chi2 | 296.42 | |
| df_m | 20 | |
| ll | -257.09 | |
| Aic | 556.17 | |

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

**Table 7: Exposure probit model and marginal effects in Guinea**

| **Variable** | **Exposure probit model** | **Marginal effect (dy/dx)** |
|---|---|---|
| Age | .0065 | 0.002 |
| Number of years resident in village | -0.002 | -0.001 |
| NERICA village | 0.387*** | 0.113*** |
| Household size | 0.011 | 0.003 |
| Being woman | -0.467* | -0.122** |
| Middle Guinea | -0.046 | -0.013 |
| Upper Guinea | 0.612*** | 0.190*** |
| Forest Guinea | -1.189*** | -0.287*** |
| Experience in upland rice farming | 0.178 | 0.050 |

| | | |
|---|---|---|
| Experience in lowland rice farming | -0.400*** | -0.108*** |
| Village contact with SG2000 | 0.173 | 0.050 |
| Total number of IRAG varieties known in the village | 0.012 | 0.003 |
| Total number of NERICA varieties known in the village | 0.462*** | 0.130*** |
| Total number of traditional varieties known in the village | -0.002 | -0.001 |
| Extension | 0.352*** | 0.101*** |
| Total number of IRAG varieties known by farmer | | |
| Total number of traditional varieties known by farmer | | |
| Contact with SG2000 | | |
| Access to credit | | |
| _cons | -1.592*** | |
| Number of sample farmers | 1467 | 1467 |
| Pseudo R2 | 0.235 | |
| Khi 2 | 448.197 | |
| Df m | 15 | |
| Log of likelihood | -731.481 | |
| AIC | 1494.962 | |

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

**Table 8: Exposure probit model and marginal effects in Benin**

| Variable | Exposure probit model | Marginal effect (dy/dx) |
|---|---|---|
| Knowledge of writing in traditional language | 0.403 | 0.135 |
| Education form | -0.193 | -0.062 |
| Within a farmer association | -0.106 | -0.034 |
| Receving training on rice | 0.080 | 0.026 |
| NERICA Village | 0.922*** | 0.316*** |
| Household size | 0.097** | 0.031** |
| Man gender | 0.395 | 0.127 |
| Age | 0.015 | 0.005 |
| Age squared | -0.000 | -0.000 |
| Log of total land size | 0.367 | |
| Number of rice varieties known | 0.163 | |
| Constant term | -2.331* | |
| Number of sample farmers | 268.00 | |
| Pseudo R2 | 0.13 | |
| Khi 2 | 46.97 | |
| Df m | 9.00 | |

| | |
|---|---|
| Log of likelihood | -151.35 |
| AIC | 322.70 |

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

**Table 9: Exposure probit model and marginal effects in Gambia**

| Variable | Exposure probit model | Marginal effect (dy/dx) |
|---|---|---|
| NERICA Village | 0.727*** | 0.269*** |
| Number of modern varieties in the village | 0.054 | 0.019 |
| Contact with NARI | 0.562* | 0.196* |
| Western Region | 0.588*** | 0.210*** |
| Household Size | | |
| basfond | | |
| Number of traditional varieties known by a farmer | | |
| Farmer contact with DAS | | |
| North Bank Region | | |
| _cons | -0.748*** | |
| Number of sample farmers | 600.00 | |
| Pseudo R2 | 0.11 | |
| Khi 2 | 89.65 | |
| Degree of freedom | 4 | |
| Log of likelihood | -369.30 | |
| AIC | 748.59 | |

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

**Table 10: Coefficients estimates of estimated parametric models for NERICA adoption and marginal effects in Cote d'Ivoire**

| Variable | ATE probit adoption model | ATE probit adoption Model (dy/dx) | Classic probit joint exposure and adoption model | Classic probit adoption Model (dy/dx) |
|---|---|---|---|---|
| NERICA village | 1.90** | 0.427*** | 1.11*** | 0.057*** |
| Village contact with ANADER | | | 0.25 | -0.010 |

| | | | | |
|---|---|---|---|---|
| Village contact with CIDT/GVC | | | -1.485* | -0.010 |
| Village contact with SATMACI/SODERIZ | | 0.075*** | 3.26*** | 0.217*** |
| Number of NERICA varieties known in the village | | 0.023*** | 1.56*** | 0.077*** |
| Number of traditional varieties known in the village | | 0.002*** | 0.01 | 0.00 |
| Number of NARS upland rice varieties known in the village | | -0.006* | -0.635*** | -0.032*** |
| Number of WARDA upland interspecific rice varieties known in the village | | | 0.31* | 0.000 |
| Past participation to PVS trials | 0 .91* | 0.210* | 0.37 | 0.033* |
| Practice upland rice cultivation | 0 .46 | 0.090 | 2.20*** | 0.037*** |
| lx5totar | -0.13 | -0.030 | 0.22 | 0.000 |
| Household size in 1996 | | | -0.06 | 0.000 |
| Being born in the same village | | | 0.35 | 0.010 |
| age | -0.01 | 0.000 | 0.0004 | 0.000 |
| Having a secondary activity | 0.45 | 0.090 | 0.57** | 0.026* |
| Years of formal schooling | -0.05 | -0.010 | 0.02 | 0.000 |
| Being woman | -0.02 | 0.000 | 0.26 | 0.010 |
| Being from Ethnie Bete | 1.12** | 0.249* | -1.86*** | -0.010 |
| Being from Ethnie senoufo | 1.71** | 0.340** | 0.03 | 0.150 |
| Being in Forest zone | | | -3.40*** | 0.040 |
| Farmer contact with CIDT/GVC | 0 .96 | 0.220 | 0.33 | 0.030 |
| Farmer contact with SATMACI/SODERIZ | 0.19 | 0.040 | 0.39 | 0.010 |
| Average Household size for the 5 past years | 0.05 | 0.010 | 0.09 | 0.000 |
| _Constant | -2.90** | | -6.92*** | |
| N | 123 | | 1261 | |
| r2_p | 0.20 | | 0.415 | |
| chi2 | 40.48 | | 107.96 | |
| df_m | 13 | | 23 | |
| ll | -64.95 | | -115.55 | |
| Aic | 157.91 | | 279.10 | |

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

**Table 11: Coefficients estimates of estimated parametric models for NERICA adoption and marginal effects in Guinea**

| Variable | ATE probit adoption model | ATE probit adoption Model (dy/dx) | Classic probit joint exposure and adoption model | Classic probit adoption Model (dy/dx) |
|---|---|---|---|---|
| Age | -0.003 | -0.001 | -0.002 | 0.001 |
| Number of years resident in village | 0.008 | 0.002 | 0.002 | 0.001 |
| NERICA village | -0.082 | -0.024 | 0.230* | 0.057* |
| Household size | 0.006 | 0.002 | 0.013 | 0.002 |
| Being woman | -0.892** | -0.264** | -0.513* | -0.138*** |
| Middle Guinea | -0.615* | -0.187* | 0.059 | -0.074* |
| Upper Guinea | -0.831*** | -0.255*** | 0.166 | -0.002 |
| Forest Guinea | 0.732* | 0.213* | -0.055 | -0.126*** |
| Experience in upland rice farming | -0.106 | -0.032 | 0.039 | 0.018 |
| Experience in lowland rice farming | -0.248 | -0.071 | -0.258* | -0.090*** |
| Village contact with SG2000 | | | 0.292** | 0.029 |
| Total number of IRAG varieties known in the village | | | -0.036 | 0.002 |
| Total number of NERICA varieties known in the village | | | 0.353*** | 0.075*** |
| Total number of traditional varieties known in the village | | | -0.016* | -0.000 |
| Extension | 0.588*** | 0.169*** | 0.457*** | 0.125*** |
| Total number of IRAG varieties known by farmer | 0.295*** | 0.087*** | 0.127* | 0.033*** |
| Total number of traditional varieties known by farmer | -0.095*** | -0.028*** | 0.025* | -0.011*** |
| Farmer contact with SG2000 | -0.145 | | -0.004 | |
| Access to credit | | | 0.261 | 0.066 |
| _cons | 0.565 | | -1.927*** | |
| Number of sample farmers | 511 | 1467 | 1467 | 1467 |
| Pseudo R2 | 0.171 | | 0.150 | |
| Khi 2 | 98.724 | | 189.886 | |
| Df m | 14 | | 19 | |
| Log of likelihood | -291.916 | | -619.814 | |
| AIC | 613.832 | | 1279.629 | |

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

**Table 12: Coefficients estimates of estimated parametric models for NERICA adoption and marginal effects in Benin**

| Variable | ATE probit adoption model | ATE probit adoption Model (dy/dx) | Classic probit joint exposure and adoption model | Classic probit adoption Model (dy/dx) |
|---|---|---|---|---|
| Knowledge of writing in traditional language | | | 0.261 | 0.064 |
| Education form | | | 0.008 | -0.030 |
| Within a farmer association | | | -0.374 | -0.016 |
| Receving training on rice | | | 0.433* | 0.012 |
| NERICA Village | 0.038 | 0.012 | 0.649** | 0.153*** |
| Household size | 0.021 | 0.007 | 0.094* | 0.017* |
| Man gender | -0.285 | -0.094 | 0.421 | 0.027 |
| Age | 0.193** | 0.064** | 0.095 | 0.025* |
| Age squared | -0.002** | -0.001** | -0.001* | -0.000* |
| Log of total land size | 0.260* | 0.122* | | 0.044* |
| Number of rice varieties known | 0.087 | 0.054 | | 0.019 |
| Constant term | -3.448* | | -4.240*** | |
| Number of sample farmers | 96.00 | | 268.00 | |
| Pseudo R2 | 0.12 | | 0.16 | |
| Khi 2 | 19.03 | | 48.41 | |
| Df m | 7.00 | | 11.00 | |
| Log of likelihood | -58.26 | | -107.86 | |
| AIC | 132.53 | | 239.72 | |

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

**Table 13: Coefficients estimates of estimated parametric models for NERICA adoption and marginal effects in Gambia**

| Variable | ATE probit adoption model | ATE probit adoption Model (dy/dx) | Classic probit joint exposure and adoption model | Classic probit adoption Model (dy/dx) |
|---|---|---|---|---|
| NERICA Village | | | 0.688*** | 0.234*** |
| Number of modern varieties in the village | | | 0.063* | 0.016 |
| Contact with NARI | | | 0.592* | 0.172* |
| Western Region | -0.820*** | -0.192** | 0.282 | 0.066 |
| Household Size | -0.012 | -0.002 | 0.001 | -0.001 |
| basfond | -0.250 | -0.043 | -0.519*** | -0.021 |
| Number of traditional varieties known by a farmer | -0.091** | -0.017*** | 0.021 | -0.008*** |
| Farmer contact with DAS | 0.555* | 0.093** | 0.182 | 0.045** |
| North Bank Region | -0.900*** | -0.217** | -0.340* | -0.103** |

| | | |
|---|---|---|
| _cons | 2.200*** | -0.600** |
| Number of sample farmers | 277.00 | 600.00 |
| Pseudo R2 | 0.13 | 0.12 |
| Khi 2 | 32.90 | 89.35 |
| Degree of freedom | 6 | 9 |
| Log of likelihood | -99.59 | -355.11 |
| AIC | 213.17 | 730.23 |

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$