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Africa's Green Revolution? The determinants of the adoption of NERICAs in West Africa

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Africa's Green Revolution? The determinants of the adoption of NERICAS in West Africa

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Abstract

We analyse the rate and determinants of adoption of modern rice varieties (NERICAs) in Guinea, The Gambia and Cote d'Ivoire. The role of knowledge and information is evaluated using programme evaluation methods. Using household data collected by the Africa Rice Centre we show that the *exposure* and *access to seeds* lead to radically different levels of adoption by country: 30% in Cote D'Ivoire compared to around 90% for The Gambia and Guinea. Analysis of the determinants of adoption in each country reveals the heterogeneity in the role of agricultural and societal conditions and implies country/province specific policies are appropriate.

JEL classification: Q16, Q18

Keywords: NERICA Varieties, Technology Adoption, West Africa, Food Security.

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1. Introduction

This paper uses modern evaluation theory to estimate the rate of adoption and its determinants of improved seed varieties in various West African countries – namely Guinea, The Gambia and Cote d'Ivoire.

West African agriculture is characterised by the effects of very low land and labour productivity. Whilst there have been some success stories, the majority of production is subsistence based – with very little scope for growth and development. Green Revolutions that pioneered and helped sustain Asian development in the 1960s have, thus far, proved elusive. To realise the potential productive capacity of West African agriculture, technology transfer to the majority of farmers is of great importance. Widespread dissemination of improved seed varieties is known to have vastly contributed to the success of agricultural production during the Asian miracle, alongside adoption of complementary inputs.

The study focuses on the dissemination efforts of NERICA – a hybrid rice variety aiming to decrease Africa’s reliance on food imports through domestic productivity improvements. However, we take for granted the potential benefits that widespread NERICA adoption could bring and concentrate on its widespread adoption. Kijima et al (2006) show that average yields could double. In Benin, incomes rose by US$277 per hectare for men and US$337 per hectare for women[1]. There was a 6% increase in school attendance rates, a 14% increase in the gender parity index and a 36kcal per equivalent adult increase in calorie intake[2]. Mosley (2002) attributes these pro-poor properties to the scale-neutrality, labour-intensity, risk-reducing, price-reducing and off-farm linkage characteristic of hybrid seeds. Of course, the magnitude of benefits depends on complementary improvements in soil management, local markets and government policies[3].

This study aims to be able to provide further insight into the mechanisms of technology diffusion. Of which, the importance of exposure, knowledge and understanding of the technology is emphasised throughout. Governments and agricultural extension agencies require a better working knowledge of the determinants and constraints to the adoption of higher-yielding agricultural technologies. We shall see that simply by telling farmers that such a technology exists and by ensuring access to it, significant levels of adoption can be observed to materialise. Of course, addressing further constraints to adoption help can influence subsequent adoption levels.

To expose such factors in the heterogeneous farming environment of West Africa, we utilise data from extensive household level surveys obtained by the Africa Rice Centre (ARC). These detail the various socioeconomic factors that are likely to influence an individual farmers decision to adopt.

We face problems in estimating accurate levels of adoption rates. Farmer knowledge of the improved varieties is not universal, thus simple observational statistics do not provide an accurate reflection of the degree of NERICA uptake across the sample. Furthermore, there is no reason to assume that the exposed group are representative of the population. We address this problem by employing a programme evaluation methodology based on counterfactual outcomes to provide unbiased estimators of the rate of adoption and the factors affecting it.

This paper contributes to the methodological framework in estimating agricultural technology dissemination, whilst providing guidance about the various constraints of adoption for agencies involved in disseminating the improved seed varieties. Unsurprisingly, our results stress the importance of understanding the heterogeneity of agricultural and societal conditions in the countries of study, such that country specific (even province specific) policies can provide better adoption results than simple generalisations.

The findings of this study highlight the importance of knowledge in determining agricultural technology transfer among West African farmers. The channels that knowledge dissipates through a population are crucial to our understanding of the adoption process. This involves comprehending the complex and intertwined roles that social learning, farmer learning-by-doing and extension services play in spreading knowledge and understanding through a population over time. We find adoption rates of NERICA high enough to stimulate widespread adoption over time. A Green Revolution in West African agriculture could be stimulated and sustained with complementary adoption of inputs. This paper inherently assumes positive characteristics of NERICAs. It is beyond its scope to assess their impact[4]. This is obviously a fruitful area of potential research.

Section 2 describes the data and evaluates the literate regarding agricultural technology adoption, whereby the role of knowledge in determining the adoption rates is emphasised. Section 3 explores the methodology undertaken to estimate unbiased rates of NERICA adoption. Section 4 reports and discusses the results of the estimation procedures. Section 5 concludes.

2. Technology Adoption: Conceptual Issues

(a) Adoption and Knowledge

NERICA adoption is dependant on farmer knowledge of their existence. Once a farmer has a complete understanding of a new technology, an informed adoption decision can be made[5]. Yet, it is quite apparent that such a situation is unlikely to be present in our scenario. After only a few years of dissemination efforts, knowledge and understanding throughout the population be limited – certainly not complete. As a result, farmers' adoption decisions will be based on varying degrees of incomplete information. We confine our definition of adoption to the growing of one or more NERICA varieties.

Perspectives on adoption processes can be classified along a number of dichotomies:[6]

- Economic structures and incentives vs. sociological influences
- Static vs. dynamic adoption
- Single stage vs. multi-stage adoption

In accommodating incomplete awareness of NERICAs, this study goes some way to bridging these dichotomies. The existence of incomplete information places emphasis on the role of social networks, communication and perceptions. In turn, this forces us to think of adoption as a dynamic process of "social learning" that occurs through the diffusion of information, building on previous experiments and anticipating long-run gains[7].

Saha et al (1994) argue that the probability of adoption (and its intensity) is boosted by information because an increased understanding of potential benefits reduces outcome risk. Similarly, where there is considerable heterogeneity in the population, more of the information regarding the determinants of other farmers' success is likely to be unobservable. It therefore cannot be used by the farmer to judge the extent to which his own adoption would produce similar gains, slowing down the adoption process. The role of social learning is argued to be particularly important for the adoption of new varieties of rice by Munshi (2004), who compares diffusion patterns with wheat and concludes that greater heterogeneity in, and sensitivity to, growing conditions for rice make the determinants of successful adoption unobservable and usable information scarce.

Possessing information is not, then, a binary variable, and its acquisition takes many forms. For instance, Dimara and Skuras (2004) distinguish passive learning from active information gathering, where farmers search out information on an innovation. However, in this analysis we focus on the initial binary stage of farmer awareness of NERICAs, as exposure is likely to be the most immediate hurdle to adoption. Nevertheless, the complexities of heterogeneity and unobservability will remain central.

(b) Traditional Determinants Theory

Kijima et al (2006) stress the importance of training and extension services to aid local adaptation. The authors also note that prior rice-growing experience generates good management practices, which increase the benefits from NERICA adoption.

While seeds are not a particularly lumpy investment[8], credit and cash constraints can be important because adoption often entails complementary investments. Ideally, of course, it is the availability of credit and cash flow that is relevant. Our data forces us to settle for the use of credit in the current period.

Doss (2006) notes the ability to hire additional labour may be essential for technology adoption. Yet, Lancon (2001) states that the use of NERICAs actually reduce the labour requirement per unit of output for weeding, a major burden of production. In product markets, expected crop prices and price-volatility are just as central. The availability of complementary inputs such as fertiliser may also inhibit adoption. Diagne (2006) note the access and availability of seed as a constraint to NERICA adoption in West Africa. Like knowledge, this is a clear prerequisite for adoption[9].

Conley and Udry (2003) show that farmers adjust their activities in line with the successful experimentation of others, so social networks are important to adoption. Bandiera and Rasul (2002) argue that while there are positive spillovers from sharing best practices, there may also be free riding in experimentation.

Asfaw and Admassie (2003) note that human capital improves “the allocative and technical efficiency of producers by exposing them to a more systematic and dynamic production system and enhances their ability to choose the optimal bundle of input and output mix”[10]. Indeed, the belief that a lack of education can be a barrier to adoption is so widespread that it has been termed the “Schultz hypothesis”[11]. This view of education as a progressive force of technological change is shared by Pingali et al (2001), who note that better educated and younger farmers are expected to be able to judge the merits of technological change to a greater degree, thus making an informed adoption decision.

When reviewing evidence on farm size, Lipton and Longhurst (1989) argue that small farmers often adopt new agricultural technologies with greater effectiveness, but that bigger farmers often take the early risks. The speed of adoption for smaller farmers is often dependant on policy. By viewing adoption as a dynamic process, there is greater opportunity to gain inference about adoption relating to farm size through the dynamics described by Lipton and Longhurst (1989). Unfortunately our study only permits the use of static observations. With such contrasting results found on the impact of farm size on adoption, Feder et al (1985) suggest that the size of holding acts as a surrogate for a large number of potentially important factors, such as access to credit, capacity to bear risks, access to scare inputs, wealth and access to information.

Mosley (1982) highlights the many sources of technological, financial and policy risk that farmers face, and the lack of formal and informal institutions in rural areas to insure against these risks. Conversely, Lancon (2001) describes the risk reducing characteristics of NERICA. This goes against the conventional wisdom of technology adoption, where higher yards usually trades off against increased production risk. Unfortunately, risk and risk-preferences are not captured in our data. Finally, individual plots may simply not be suited to NERICAs. Unfortunately, accommodating plot-level variability is not possible with our datasets.

Interestingly, some characteristics of NERICA do not conform to theories of agricultural technology adoption described above. This is likely to have intriguing effects on our results and the dynamics of adoption.

3. Empirical Methodology

In this section we describe the empirical issues associated with identifying and estimating adoption rates using ex-post non-experimental data. The key explanatory variable of interest here is that of knowledge of NERICA varieties. In addition to selection bias, which is pervasive in the evaluation of programmes, the use of knowledge as the ‘treatment’ variable introduces another form of bias: *non-exposure bias*. The presence of such biases means that typical estimators of adoption rates, such as the observed sample adoption rate and the exposed sample adoption rates, are almost certainly misleading (e.g. Spencer 2006). Alternative estimators need to be identified.[12]

(a) Selection Bias and Non-Exposure Bias

The observed sample adoption rate[13] can be observed to underestimate the population adoption rate, as it doesn’t take into account the members of the sample that potentially would adopt had they been exposed to the treatment. The difference between this and the true adoption rate is referred to as the non-exposure bias. As a result, the sample adoption rate only accounts for the members of the sample that have acquired knowledge of NERICAs and have adopted.

Unexposed farmers *cannot* adopt, even if they would have chosen to on being made aware of NERICAs; the observed adoption response for these individuals is censored and the full-sample adoption rate is biased downwards. As knowledge of NERICA is a necessary precondition for adoption, the sample adoption rates of 39.5%, 19.8% and 3.5% in Gambia, Guinea and Côte d'Ivoire respectively underestimate the true population adoption rate.

Intuitively, it may appear as if taking the adoption rate among the sub-sample of farmers exposed to the technology would give a consistent estimate of the population adoption rate. However, this approach is also problematic. Here the problem is selection bias since exposed farmers are not representative of the population.

Selection bias can occur through three mechanisms. Firstly, farmers with more to gain from a technology may actively search for its existence, self-selecting themselves for exposure. This emphasises the fact that exposure to a new technology is partly a choice, and thus is unlikely to be random throughout the population. Secondly, gaining knowledge of a technology can also occur through informal 'social networks', where better-connected farmers may have a higher propensity to be exposed. Finally, knowledge is also actively disseminated by research and extension agencies to targeted populations. Individual farmers more predisposed to technology adoption can be actively targeted by agencies, resulting in farmers more likely to adopt being in the exposed sub-sample.

These scenarios describe *positive* selection bias. Diagne and Demont (2007) argue that agricultural technologies, like NERICAs, are likely to exhibit these properties. Having said that, there is no theoretical reason why *negative* selection bias could not be observed, where those exposed to the technology would be less likely to adopt than the rest of the population. Such a case could be achieved through extension agencies targeting such individuals – perhaps with the aim of reducing poverty, rather than maximising adoption.

Restricting the sample to only those farmers with knowledge of NERICA gives estimators of the rate of adoption of 85.5% for Gambia, 55.5% for Guinea and 37.9% for Côte d'Ivoire. Selection bias causes this estimator to be unrepresentative for the population as a whole. There is no reason to assume that the propensity of adoption is the same in both exposed and unexposed sub-samples. The same problem afflicts the identification of barriers to adoption, since the circumstances faced by the exposed non-adopters may not be representative. We require the use of programme evaluation techniques to estimate a consistent estimator of the adoption rate and its determinants throughout the population.

(b) The identification problem

We now describe these empirical problems more formally within a counterfactual framework with a view to identifying alternative estimators of adoption. The biases arise from observing only exposed farmers' adoption responses. We essentially face a missing data problem from not knowing whether an unexposed farmer would adopt were they to learn about the existence of NERICAs. A counterfactual framework allows us to examine all possible responses[14].

Let D_i be a binary treatment variable, where 1 denotes farmer exposure to NERICA; 0 otherwise. $y_i(1)$ refers to the potential adoption outcome when a farmer is exposed to the treatment[15], $y_i(0)$ the outcome in the state of no knowledge of NERICAs. The outcome variable is a binary indication of whether or not a farmer adopts at least one variety of NERICA.

The measure $y_i(1)-y_i(0)$ would provide the ideal measure of the impact of NERICA knowledge on each individual. However, an identification problem arises due to the fact that we cannot observe both of the potential outcomes $y_i(1)$ and $y_i(0)$ for the same individual. The observed data is realised via a switching equation: $y_i = y_i(0)+D_i\left(y_i(1)-y_i(0)\right)$. This relationship provides the basis of identification and estimation of the various treatment effects as we show below.[16]

An interesting characteristic of technology adoption in this case is that $y_i(0)=0$ for all individuals. This reflects the impossibility of adoption without knowledge of the innovation. The identification problem remains however since we do not observe $y_i(1)$ for both treated and untreated.

Typically identification strategies attempt to identify summary population measures of the individual level impacts. The Average Treatment on the Treated (ATE) is usually the focus of attention: $E\left[y_i(1)-y_i(0)\right]$ For NERICA adoption, ATE estimates the probability of adoption after exposing a randomly selected farmer to NERICA, thus representing the *potential* adoption rate under complete knowledge of NERICAs.

Additional measures of im act include the Average Treatment Effect on the Treated (ATT): $E\left[y_i(1)-y_i(0)\mid D_i=1\right]$ and the Average Treatment Effect on the Untreated (ATU): $E\left[y_i(1)-y_i(0)\mid D_i=0\right]$.[17] The former measures the expected effect of treatment on a person randomly chosen from the exposed sub-population, the latter measures the expected effect of treatment on the unexposed sub-population. We are arguably more interested in the ATU than the ATT, as the ATU illustrates the potential of further adoption, were knowledge to diffuse to the unexposed population. A low value of the ATU would therefore question further effort of extension agencies to spread knowledge of NERICAs existence. When selection bias between treatment groups is not present, these three estimators will equate. The identification of these treatment effects requires some additional assumptions.

(c) Assumptions for the identification of adoption rates

A typical starting point is to assume \`strong ignorability', which consists of two assumptions: conditional independence and overlap (Rosenbaum and Rubin, 1983). To explain these assumptions assume X_i is a vector of covariates influencing an individual's decision to adopt, and Z_i is a vector of covariates influencing exposure, which includes X_i.

i) Conditional Independence

Conditional independence is defined as:

$$y_i(1), y_i(0) \perp D_i \mid X_i \quad (1)$$

Where the symbol $\perp$ reads as 'is independent of'. This means that once one has controlled for observable differences between treated and untreated, the treatment is independence of the potential outcomes. [18] Controlling for variations between treatment groups is motivated by the need to eliminate selection bias between the exposed and unexposed subpopulations. In order for this assumption to be plausible, the observable characteristics in X_i must give a sufficiently strong representation of the factors influencing exposure. Recent work has pointed out that in conditioning on observable variables one should not condition on too many variables (Wooldridge, 2009), and one should avoid conditioning on variables that may be affected by the treatment itself via feedback (Heckman, 2010). Conditional independence allows the unknown counterfactuals for the untreated group to be inferred from the known conditional outcomes for the treated group and vice versa. In fact, the weaker assumption of conditional mean independence is all that is required for the estimators we use here (Wooldridge 2006, Ch 21).

ii) The overlap assumption

Another condition for identification of treatment effects is overlap (e.g. Wooldridge 2006, Ch 21):

$$0 \le P\left(D_i = 1 \mid X_i = x\right) \le 1 \quad \forall X_i \tag{2}$$

For all possible values of covariates, we require both treated and control units[19]. Overlap is required to ensure that the covariate distributions overlap (given their treatment status) and are comparable between the treated and untreated groups. Together these assumptions are termed 'strong ignorability'. If 'strong ignorability' holds an estimate of ATE purged of non-exposure and selection bias can be obtained using observational data.

iii) The SUTVA assumption

One further assumption that is typically made in the programme evaluation literature is the Stable Unit Treatment Value Assumption (SUTVA). In essence this means that there are no spill-overs of adoption from one farmer to another. does not affect the adoption outcome of others. The extent to which this is a major simplification is debateable. On the one hand Holloway et al (2002) identify positive neighbourhood effects from the adoption of high-yielding rice in Bangladesh, while Besley and Case (1993) illustrate the importance of demonstration effects and social networks in West Africa. On the other hand, Suri (2010) argues that the spillover effects of adoption are relatively minor in Kenya. Perhaps a more pervasive problem with conditional independence is that unobserved characteristics drive the adoption decision. In such cases, different identification assumptions are required.

(d) Other empirical considerations

The role of covariates under strong ignorability therefore cannot be understated. It is imperative that the relevant variables are incorporated into a set of covariates to attempt to account for the variability between the treatment and control groups, thereby ensuring conditional independence and overlap hold.

A general rule to balance the treatment and control groups through conditioning on covariates is to control for the pre-treatment covariates[20]. However, Heckman and Vytlacil (2005) argue that covariates can also be endogenous and not discredit the model's causal inference, as long as an assumption is made whereby the covariates would have been the same between the treated and untreated groups almost everywhere[21]. Formally;

$$\left(X_i \mid D_i = 1\right) = \left(X_i \mid D_i = 0\right) \text{ almost everywhere} \quad (3)$$

The variables that satisfy these conditions are those that are generally determined before exposure occurs *and* remain unchanged after exposure.

4. Identification and Estimation of Adoption Rates: The Knowledge Treatment Effect

In this section we describe the identification strategy under strong ignorability. This leads to two estimators that we ultimately use to estimate the rate of NERICA adoption in Guinea, The Gambia and Cote D'Ivoire. Appendix 1 and 2 provide more details.

(a) The inverse propensity score weighting estimator (IPSW)

The reason that simple analyses of adoption are likely to be misleading is because of selection bias and non-exposure bias. In essence this arises because the realised data on adoption reflects not adoption itself, but the joint realisation of knowledge of the technology and adoption (Diagne and Demont 2007). In terms of the switching equation:

$$\begin{aligned} y_i &= y_i(0) + D_i\left(y_i(1) - y_i(0)\right) \\ &= D_i y_i(1) \end{aligned} \tag{4}$$

whereas the measure of interest at the individual level is $y_i(1)$ and the ATE, i.e. the adoption rate in the population, is $E\left[y_i(1)\right]$. This illustrates the problem with using the sample average as a measure of adoption rates (e.g. Dorward et al. 2006).

Assuming that Z_i is a vector of conditioning variables that is different from and yet contains X_i, Diagne and Demont (2007, p204) demonstrate that the ATE of knowledge can be identified using (4) under the following additional assumptions: i) potential adoption is independent of Z_i, conditional on X_i: $P\left[y_i(1)=1 \mid X_i, Z_i\right] = P\left[y_i(1)=1 \mid X_i\right]$; ii) Exposure is independent of X_i, conditional on Z_i: $P\left[D_i(1)=1 \mid X_i, Z_i\right] = P\left[D_i(1)=1 \mid Z_i\right]$; and, iii) Overlap in Z_i: $0 < P\left[D_i = 1 \mid Z_i\right] \le 1$. In essence, assumption i) means that the variables in Z_i but not in X_i must only affect adoption via the knowledge variable D_i. Assumption ii) holds by definition of Z_i and X_i. Under these assumptions Appendix 1 shows that ATE can be identified as follows:

$$ATE = E_x\left[E\left[y_i \mid X_i\right] / p\left(Z_i\right)\right] \tag{5}$$

This is the so-called inverse propensity score weighting estimator (IPSW) of Diagne and Demont (2007) which is non-parametrically identified. Intuitively, all that this estimator does is correct the observed conditional adoption rates by dividing through by the conditional likelihood of exposure to the technology.

In order to implement this estimator we employ the semi-parametric approach proposed by Diagne and Demont (2007, p.204) to estimate ATE, ATU and ATT. Equation (5) implies that an estimate of ATE can be obtained as follows:

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{m}\left(x_i\right)}{\hat{p}\left(z_i\right)} \tag{6}$$

where $\hat{m}\left(x_i\right)$ is an estimate of the conditional expectation of adoption and $\hat{p}\left(z_i\right)$ is an estimate of the propensity score for knowledge of NERICAs. We use OLS to estimate the former and a probit model to estimate the latter. A semi-parametric approach can be used to estimate ATE here, by substituting $\hat{m}\left(x_i\right)$ for y_i in (5). This has some advantages as discussed below.

(b) Matching estimator

For comparative purposes and as a check of the robustness of the IPSW approach, we also use a matching technique to impute the missing potential outcomes for the untreated group using average outcomes for individuals with similar observed characteristics in the treated group. Following the same methodology proposed by Imbens et al (2004, p.293-4), we restrict the number of matches for an individual to one, and assume that $c < P\left(D_i = 1 \mid Z_i = z_i\right) < 1 - c$, for some c > 0, alongside strong ignorability. These assumptions allow the identification of the counterfactual $y_i(1)$ for the untreated group. Individuals are matched to another farmer such that the distance between the opposing covariates of treatment groups are minimised. Then, treatment effects are estimated as follows:

$$AT\hat{E}^{NN} = \frac{1}{n}\sum_{i=1}^{n}\left\{\hat{y}_i(1)\right\} = \frac{1}{n}\sum_{i=1}^{n}\left(2D_i - 1\right)\left\{1 + K_{iM}\right\} y_i \tag{7}$$

Our use of matching to balance the covariates between groups is an intuitive way to account for treatment effects within a sub-sample. Yet, limited overlap in the covariate cells between treatment groups can prevent the success of matching techniques as it reduces the likelihood of similar covariates for potential matches.

Furthermore, if the dimension of X_i is large, conditioning on exactly the same value of X_i can result in too few observations for each subpopulation[22]. Through adherence to conditional independence, we create conditions not conducive to efficient exact-matching, especially in a heterogeneous population. In a situation where many factors have to be conditioned for to satisfy conditional independence, having a high-dimensioned X_i is likely to reduce the cell size of a matching estimator.

If high dimensions of X_i are to be an empirical problem, matching can be observed to work better when the control group is much larger than the treated group[23]. Thus, estimates obtained for Côte d'Ivoire are likely to be more efficient that those for Guinea and Gambia, where there are smaller proportioned control groups, *if* limited overlap is present *and* affects the matching process.

(c) Discussion of estimators

The use of semi-parametric approaches: IPSW and nearest neighbour PS matching, to the estimate treatment effects is motivated by problems associated with linearity assumptions and *quasi-complete separation* of parametric models in the context of new technology adoption.

Since $y_i(0) = 0$, parametric estimation by probit or tobit models is prohibited because the cell ($D_i = 0, y_i = 1$) of the permutation matrix is empty and coefficients are consequently infinite[24].

Furthermore, parametric estimators are likely to be very sensitive to linearity assumptions. This is exacerbated in the $y_i(0) = 0$ case because the standard covariate term is redundant and the linearity must be extrapolated solely from the interaction term relating to the treated group; linearity is forced to do a lot more of the 'work'. The problems associated with linearity assumptions also beset standard linear procedures for dealing with selection on unobservables like two stage least squares.

On the down side, estimation based on the propensity score can reveal underlying difficulties in its application, particularly regarding a lack of common support and overlap between treatment groups. Crump et al (2009) describe how estimation using the propensity score can be subject to inadequate common support between values of the propensity score approaching zero and one. Overlap between treatment and control groups is required for all covariate distributions. Without this, estimators cannot effectively control for covariates between groups since the counterfactual data is essentially missing data, resulting in a potential source of bias and large variances. As a general rule, they suggest trimming individuals outside the bounds of $0.1 < p(z_i) < 0.9$ to achieve substantial gains in efficiency[25]. Dropping observations near the extremes of the propensity score ensures that regressions are estimated using only covariate cells where there are at least a few treated and control observations[26]. They further argue that the external validity of results should not be affected, as farmers with very high or low probability of treatment are less likely to be representative of the population.[27]

For our purposes, we choose conditioning variables to account for the factors influencing exposure and adoption based on the technology adoption literature and the necessity to adhere to the 'strong ignorability' condition. In order to be able to compare the determinants of knowledge and adoption we use similar categories of variable for each country. These describe socio-economic attributes, farm characteristics, farmer knowledge and interactions with extension agencies. Lastly, country specific variables are also used to account for some of the inevitable heterogeneity between and within countries.

Where conditioning variables have the potential to be influenced by adoption, such as rice income, rice area farmed and upland rice experience, we data lagged one year prior to the adoption survey to minimise post-treatment effects on the explanatory variables.[28]

(d) Constraints to exposure and adoption

Agricultural technology adoption can be studied as a two-stage process. Firstly, farmers acquire knowledge about the technology. Secondly, an adoption decision is made. Knowledge is a prerequisite for adoption. Each stage is fraught with its own particular constraints and difficulties, and a study of technology adoption would not be complete without some analysis of the features that determine each.

We estimate the factors affecting adoption, by initially estimating the factors influencing exposure to NERICAs. The first-stage probit estimation of the propensity score in the IPSW estimator is used to identify the magnitude of the factors influencing a farmers' exposure to the technology. The determinants of adoption are analysed using estimates of their effect on adoption *after* conditioning for exposure to NERICA, in a similar way to those given in Diagne and Demont (2007) for Cote d'Ivoire. Given the structure of the conditioning variables, Z_i and X_i, the influence of particular variables in X_i can be analysed in both decisions. In particular, we model heterogeneity A parametric probit model conditioning for exposure is used. The results illustrate the constraints to NERICA adoption, given that farmers are already exposed.

5. Results

This section presents a description of the data and the results of our analysis. To emphasise the heterogeneity of the countries studied, in presenting the results we first compare estimates of adoption rates between countries, then look within countries to study the varying factors that affect both exposure and adoption.

(a) Africa Rice Data

Extensive surveys carried out by ARC provide the data to be analysed. Randomly selected farmers in chosen villages were surveyed in each of the three countries. This occurred approximately four years after the introduction of NERICA to the country – the dissemination efforts should therefore be at roughly the same stage in all countries.

The data for Gambia measures the NERICA exposure and adoption status for 600 farmers from 70 villages in the year 2006, along with detailed records of important socio-economic variables determining both exposure and adoption. Farmers were chosen based on multi-stage stratified sampling of villages across the six agricultural regions in the country. In each region, half of the villages selected were villages in which NERICA was actively introduced. It is this non-random aspect of sampling that requires the use of program evaluation techniques to give efficient estimators of the adoption rate. Simple analysis of the data shows that 46% of the sample had knowledge of at least one NERICA variety. 40% of the sample had adopted at least one variety. Thus, the proportion of farmers that have adopted given exposure is 86%. This is likely to be a biased estimate of the population adoption rate due to selection bias.

1467 farmers were surveyed over 79 villages in Guinea. NERICA exposure, adoption status and other socioeconomic variables were recorded in 2001, four years after dissemination started. 36% of sampled farmers had been exposed to NERICA, whilst 20% had adopted at least one variety. This gives an adoption rate given exposure of 56%.

In Côte d’Ivoire, village-level selection ensured “key sites” where ARC had been carrying out extension activities were included. These sites constituted 32 of the 50 villages in the survey. 30 rice farmers were randomly selected in each village to give a sample of 1,500. Only 11% of the full sample had knowledge of NERICAs, whilst 4% of those sampled had adopted at least one variety of NERICA. The proportion of exposed farmers that have adopted is 36%.

As farmers were only chosen randomly *after* villages and regions were taken into account, the survey is likely to suffer from selection bias because all farmers in the country were not selected randomly. The covariates are unlikely to be balanced between treatment groups.

(b) Adoption and Potential Adoption of NERICAs: Results

Table 1 shows estimates for the ATE, ATT and ATU for both estimators in all three countries. Table 2, 3 and 4 represent estimates for the determinants of exposure and adoption for Gambia, Guinea and Côte d'Ivoire respectively.

Table 1. Estimation of Adoption Rates in Gambia, Guinea and Côte d'Ivoire[29]

	Gambia				**Guinea**				**Côte d'Ivoire**			
Estimator			*95% CI*				*95% CI*				*95% CI*	
IPSW	**ATE**	90.2%	0.742	1.061	**ATE**	57.8%	0.503	0.653	**ATE**	40.1%	0.284	0.518
	ATT	87.9%	0.661	1.120	**ATT**	54.6%	0.449	0.642	**ATT**	35.4%	0.238	0.470
	ATU	93.5%	0.769	1.060	**ATU**	60.6%	0.520	0.692	**ATU**	42.0%	0.288	0.552
NNM	**ATE**	85.8%	0.820	0.917	**ATE**	52.6%	0.469	0.583	**ATE**	38.5%	0.271	0.500
	ATT	85.6%	0.798	0.913	**ATT**	55.4%	0.479	0.630	**ATT**	35.7%	0.255	0.458
	ATU	86.1%	0.824	0.935	**ATU**	51.0%	0.442	0.578	**ATU**	38.9%	0.265	0.513

The most striking result from Table 1 is the significant disparities of average treatment effects between countries. Averaging the estimations, Gambia has an adoption rate of 88%, Guinea of 55% and Côte d'Ivoire of 39%. With observed sample adoption rates of 40%, 20% and 4% respectively, we can conclude that not accounting for farmer exposure to the technology is likely to provide vast underestimates of the true population adoption rate as non-exposure bias is very large. Also, as exposure increases, the observed population sample rate converges to the population adoption rate.

This compares to adoption rates among the exposed of 86%, 56% and 36% respectively, suggesting little, if no, selection bias. Indeed, testing for selection bias yields no significant results at the 5% level. Yet, whilst there may be no *statistically significant* evidence of selection bias magnitude, there appears a definite trend in its direction. 5 out of the 6 estimates imply a small amount of negative selection bias (where the ATU > ATT). Although tiny, this contradicts most of the theory presented, which strongly suggested that farmers with the most information, assets and experience were more likely to be in the treated group.

Such results fail to adhere to the suggested hypothesis that positive selection bias is likely to persist in the population. Our results describe a scenario where individuals in the treatment and control groups have the same probability of adopting NERICA when exposed to it. The mechanisms of knowledge transfer we identified certainly support the likelihood of positive selection bias[30], but can also be used to explain its absence. The magnitude of positive selection bias from self-selection and social networks must have been cancelled out by the negative selection bias created by active targeting from extension services. This could either be from targeting farmers who would benefit the most form adoption[31], or from very poor dissemination selection. Recall that around half of each sample live in a NERICA introduction village, where NERICA exposure was induced in an artificial manner. The fact that farmers who are still unaware of NERICA have a slight higher propensity of adoption shows a lack of success in initially identifying those most likely to adopt. Yet, for such results in occur in three different countries is rather striking.

Furthermore, the lack of positive selection bias in the samples could reveal complications in technology diffusion through the channels initially identified. This suggests a greater role for extension agencies in spreading knowledge of NERICA to correct for informational market failures, along with better identification of farmers with a higher propensity of adoption. Future research must focus on farmer level impact of NERICA adoption, much like Kijima et al (2006), to identify the gains of adoption. Ideally, a framework that incorporates exposure, adoption and impact would be used to analyse the impact of NERICA. However, impact studies are often beset with both methodological and empirical difficulties[32]. Poor impact in these countries of study would suggest poor targeting of extension services.

To gain a better understanding of the results and identify potential sources of selection bias failings, we look into the factors affecting both exposure and adoption in all the countries.

(c) Determinants of Adoption and Exposure in Gambia

Table 2 shows estimates for both the determinants of exposure and adoption of NERICA in Gambia. Formal schooling can be seen to be important to both exposure and adoption of NERICA by rice farmers. As only 17% of those sampled received at least primary education, there is plenty of scope to suggest improving rural access to education, which can be seen to significantly influence a farmer's propensity to be exposed to the technology, then to subsequently adopt it. This is only likely to affect technology uptake in the long term. In the short term, dissemination efforts to target those with at least primary education could prove fruitful.

Unsurprisingly, those who adopt other modern varieties of seed (in this case NARS upland varieties) are more likely to adopt. The results also emphasise the important role of various institutions in the diffusion (NARI[33]) and adoption (DAS[34]) of NERICA. Social networks and the information gained from them appear to positively influence a farmers' chance of exposure. Farmers' that know more of the varieties grown in the village are more likely to be exposed, whilst village knowledge of NERICAs predictably increases the probability of exposure to an individual farmer.

The constraints to exposure and adoption are generally consistent with the theory discussed in Section 2. Interestingly however, older farmers are found to have a higher propensity of adoption. Gambian women also appear to have a lower probability of exposure to NERICA, but once exposed, show no difference in adoption rates.

Table 2. Factors affecting NERICA exposure and adoption in Gambia[35]

Gambia Covariates	Coefficients of Exposure		Coefficients of Adoption	
Female	-0.914***	(0.312)	0.457	(0.280)
Household size	0.003	(0.006)	0.000	(0.007)
Has formal schooling	0.678***	(0.260)	0.630*	(0.369)
Age	-0.004	(0.006)	0.013**	(0.006)
Agricultural income in 2005 (D1,000 Dalasis)	0.003	(0.008)	-0.003	(0.010)
Log of rice area in 2005, in Ha.	-0.014	(0.048)	0.061	(0.058)
Percentage of village varieties known by farmer	2.934***	(0.466)	-0.516	(0.488)
Farmer adoption of NARS upland varieties in 2006	0.182	(0.152)	0.400**	(0.192)
Number of traditional varieties known by farmer	-0.023	(0.030)	-0.026	(0.031)
Farmer contact with National Agricultural Research Institute (NARI)	0.826**	(0.368)	-0.138	(0.337)
Farmer contact with Dept Agricultural Services	0.062	(0.171)	0.495*	(0.266)
Farmer received extension advice	-0.215	(0.219)	-0.008	(0.337)
Farmer has experience in upland rice farming	0.206	(0.150)	0.272	(0.184)
Farmer access to credit facilities	0.495	(0.698)	-0.017	(0.622)
Number of NERICA varieties known in the village	2.230***	(0.297)		
Number of NARS upland varieties known in the village	0.081	(0.080)		
Village where NERICA was disseminated	-0.039	(0.152)		

(d) Guinea

Table 3 suggests various important factors in the successful dissemination of NERICA throughout Guinea. As hypothesised in Section 2, NERICA adoption and exposure in Guinea is heavily influenced by the role of various agricultural institutions and a farmers' awareness of rice growing alternatives.

Regarding exposure to NERICA, all village level covariates are highly positively significant, along with contact with government agencies and awareness of other varieties being grown in the village. A noticeable result here is that a living in a prefecture where NERCIA was introduced is still a significant variable explaining exposure *whilst* controlling for villages where NERICA was introduced *and* extension activities. This emphasises the importance of inter-village diffusion of NERICA knowledge – thereby suggesting social learning is widespread and active between villages, not just within.

Unsurprisingly, contact with ARC increases the likelihood of adoption. Yet, this has no impact on exposure. Farmers who adopt other modern varieties (NARS) also have a higher propensity to adopt NERICAs. A policy of disseminating free seeds also positively affects their adoption. The success of the policy will obviously depend on its effectiveness to maintain adoption when the subsidy has been removed in the long run.

Interestingly, having larger revenue from rice farming and a smaller rice farming area both reveal a higher propensity of exposure and adoption. Such a finding perhaps suggests that exposure and adoption rates are higher for farms with higher levels of productivity if these processes act together. It is plausible that farms with better technologies such as fertilisers or pest management techniques are more likely to be exposed to, and adopt, new seed varieties also. Certainly the evidence on farm size is particularly striking, due to the confusing and conflicting evidence regarding farm size in the technology adoption literature.

Table 3. Factors affecting NERICA exposure and adoption in Guinea[36]

Guinea Covariates	Coefficients of Exposure		Coefficients of Adoption	
Female	-0.194	(0.219)	-0.806**	(0.335)
Household size	0.014	(0.010)	0.005	(0.012)
Has formal schooling	0.059	(0.140)	0.191	(0.182)
Age	0.004	(0.004)	-0.003	(0.004)
Rice income in 2000 (FG10,000 Guinean Francs)	0.004**	(0.002)	0.017***	(0.006)
Log of rice area in 2000, in Ha.	-0.111***	(0.024)	-0.080***	(0.030)
Percentage of village varieties known by farmer	2.200***	(0.284)	-0.584*	(0.334)
Farmer adoption of NARS upland varieties in 2001	-0.024	(0.113)	0.340**	(0.141)
Number of traditional varieties known by farmer	0.014	(0.011)	-0.010	(0.014)
Farmer contact with Government institution	0.457**	(0.195)	-0.130	(0.262)
Farmer contact with ADRAO/ARC	-0.248	(0.891)	1.359***	(0.328)
Farmer received extension advice	-0.378*	(0.194)	0.143	(0.268)
Farmer from upper agro-ecological zone	0.369***	(0.133)	-0.525***	(0.169)
Farmer from forest agro-ecological zone	-1.194***	(0.228)	0.397	(0.272)
Farmer received free seeds from any institution	0.191	(0.145)	0.351**	(0.179)
Farmer contact with SG2000	0.149	(0.310)		
Farmer access to credit facilities	0.128	(0.395)		
Number of NERICA varieties known in the village	0.561***	(0.060)		
Village where NERICA was disseminated	0.357***	(0.105)		
Prefecture hosting a NERICA introduction village	1.475***	(0.390)		

Being male can be seen to positively affect the rate of adoption. This is an interesting result, as women are generally the main rice farmers in a household. Such a result can possibly be explained by the small percentage of women sampled (only 6%). As surveys were based on a household, it may be the case that males were answering on behalf of the female for matters of rice production, thus giving inaccurate results relating to gender, but accurate for the household. However, aspects of NERICA production have be reported to be relatively disadvantageous for production by females in Guinea[37], which could explain a lower propensity of adoption for female farmers.

Agro-ecological regions also affect NERICAs exposure and adoption, with the 'forest' region negatively affecting exposure and the 'upper' region positively affecting exposure, but negatively affecting adoption. Farmers better informed about the rice varieties farmed in the village are less likely to adopt. Whilst, extension advice can be seen to negatively affect the chance of exposure.

(e) Cote d'Ivoire

Unlike Gambia, females have a higher propensity of exposure in Côte d'Ivoire, whilst those in smaller households are also more likely to become aware of NERICA. A greater knowledge of traditional varieties also increases the probability of exposure.

Contact with ARC and village involvement with Participatory Varietal Selection (PVS) NERICA trials can also be seen to be significant determinants of both exposure and adoption.

Practice in upland rice farming unsurprisingly has a positive effect on NERICA adoption, yet, counter-intuitively; knowledge of more other modern varieties (NARS upland varieties) has negatively affects NERICA adoption. Differing adoption propensities among ethnicities likely reflect geographical differences in the sample, much like the forest zone.

Table 4. Factors affecting NERICA exposure and adoption in Côte d'Ivoire[38]

Côte d'Ivoire Covariates	Coefficients of Exposure		Coefficients of Adoption	
Female	0.295*	(0.162)	0.139	(0.315)
Household size	-0.034*	(0.020)	0.022	(0.045)
Has formal schooling	0.053	(0.165)	-0.062	(0.309)
Age	0.010	(0.006)	0.002	(0.013)
Agricultural income in 1999 (CFA1,000 francs)	0.002	(0.003)	-0.004	(0.004)
Log of rice area in 1999, in Ha.	0.056	(0.158)	-0.003	(0.330)
Number of NARS upland varieties known by farmer	0.073	(0.083)	-0.421**	(0.154)
Number of traditional varieties known by farmer	0.029*	(0.016)	-0.006	(0.024)
Farmer contact with ADRAO/WARDA	0.533***	(0.190)	1.345***	(0.419)
Farmer contact with ANADER	0.220	(0.317)	0.642	(0.463)
Farmer from forest agro-ecological zone	1.043	(1.073)	-2.556**	(1.158)
Farmer is ethnic Bete	-0.359	(0.424)	-1.167*	(0.699)
Farmer is ethnic Senoufo	0.116	(1.075)	-1.520*	(0.823)
Farmer is ethnic Yakouba	0.204	(0.449)	-2.488***	(0.660)
Farmer practices upland rice cultivation	0.189	(0.287)	1.703**	(0.745)
Village participation in PVS trials	0.882***	(0.272)	2.226***	(0.857)
Number of NERICA varieties known in the village	0.071	(0.086)		
Number of traditional varieties known in the village	0.013	(0.011)		

(f) Identifying Target Groups for Fast Adoption

While we have separated the determinants of exposure and adoption to highlight the different dynamics of each, in practice ARC is concerned with achieving both. Identifying "adopter types" who do not face strong barriers to adoption, but have yet to be exposed to knowledge of NERICAs can target 'Quick wins'. A focus on disseminating information to this target group could be a cheap and effective means of boosting NERICA adoption. Of course, some characteristics are conducive to both awareness and adoption. The interesting characteristics are those which are conducive to adoption but which have a broadly neutral or negative impact on the probability of exposure. Thereby targeting farmers that would be unlikely to be exposed 'naturally'.

In Guinea, such farmers are male, already farm using NARS upland varieties and are not in the 'upper' agro-ecological zone. These farmers can be conduced to adopt by offering free seed trials. 'Quick wins' can be had in Gambia by targeting older farmers who have adopted NARS upland varieties and been in contact with the Department of Agricultural Services. The evidence suggests that experience upland rice farmers should be targeted in Côte d'Ivoire, to those who do not live in the forest agro-ecological zone and have a poor knowledge of NARS upland varieties.

Such artificial exposure would effectively bypass the constraints to exposure. Therefore, targeting farmers with a higher propensity of adoption that are unlikely to be exposed otherwise could have a positive short term increase in adoption. Such intervention is also likely to further dissipate knowledge of NERICAs through social networks and the informal channels previously discussed – thereby affecting long run adoption rates also.

6. Conclusions

For a green revolution to occur in Africa, the widespread adoption of high-yielding varieties of seed will be an integral part. Understanding the dynamics behind adoption at the farmer level is therefore of great interest to those overseeing disseminating efforts. This study contributes to our understanding of the factors truly influencing the rate of adoption in the areas studied. Due to the heterogeneity of farming conditions throughout the continent, few generalisations can be made to formalise our understanding of these dynamics. It is this factor that makes the study of country-specific determinants all the more crucial to further our understanding.

Our study proposes six major conclusions: First, adoption rates are sufficiently high enough to suggest that widespread adoption could stimulate and support a Green Revolution. Adoption rates are 88% in Gambia, 55% in Guinea and 39% in Côte d'Ivoire. It should be stressed that NERICAs could not constitute a Green Revolution on their own; but with complementary innovations in other areas such as fertilizer application, farm management and in labour markets, there is a unique opportunity to boost West African agricultural productivity. Furthermore, adoption rates are not static. It is likely that barriers to adoption will fall over time, as understanding of the technology increases. As parameters inevitably change, long-term adoption rates are likely to be higher. Diagne (2006) estimates the long-run adoption rate of NERICAs in Côte d'Ivoire to be 76%.

Second, observations of population adoption rates do not provide an accurate representation of NERICA uptake or its determinants. Non-exposure bias was large in Guinea, Gambia and Côte d'Ivoire, as knowledge is essential in determining NERICA adoption. Such a fact is especially apparent in Gambia, where around 86% of those exposed go on to adopt. Through complementary interactions, the diffusion of knowledge through social networks and extension agencies can be seen to increase adoption rates on their own. This rate can be further increased through a deeper understanding of the other constraints to adoption.

Third, selective targeting could have been better utilised to increase adoption rates in all the countries studied. The evidence of no positive selection bias suggests that ARC and other extension agencies could have done more to maximise NERICA adoption by targeting farmers with a higher propensity for adoption. Little evidence of selection bias implies that those exposed have the same chance of adopting as those not exposed. Current total adoption could have been higher had extension agencies dispersed knowledge of NERICAs among farmers with a higher probability of adoption, once exposed.

Fourth, both social learning and structural constraints determine adoption patterns. The diffusion of awareness and adoption share important channels; organisational membership and extension services matter beyond their role in raising awareness. Yet, they also follow somewhat different dynamics. Social networks – in the form of education, organisational membership and contact with extension agencies – are the principal determinants of awareness while structural factors such as farm organization, asset ownership and technical support matter more for adoption. The implication for the theoretical debate is that social and structural theories of adoption should be considered complementary and be embedded in the broader framework adopted here.

Fifth, the uses of certain estimation techniques have to be evaluated to fit the correct context. We found problems associated with a lack of covariate overlap, forcing remedial measures to be taken when using the propensity score estimator. After dropping observations with exposure probabilities of either above 90% or below 10%, our estimator yields more efficient estimates with lower standard errors. Matching estimators are also susceptible to the dimension problem, when modelling under 'strong ignorability' assumptions.

Sixth, by identifying farmers with low probabilities of exposure, but higher rates of adoption once exposed, extension agencies can disseminate information to such farmers for a cheap and effective way of boosting NERICA adoption. In Gambia, knowledge should be propagated to older farmers who use modern varieties and have contact with government extension agencies. In Guinea, targeting male, lowland farmers who already use modern varieties may be effective. Extension services may wish to focus on experienced upland farmers with poor knowledge of modern varieties in Côte d'Ivoire.

This paper attempts to reconcile the methodological difficulties of modelling the dynamic process of technology adoption with the use of static data. Future research could certainly add to our understanding of these dynamics through the use of panel data to study farmer's actions over time. The important role knowledge plays in the adoption process is emphasised throughout. Whilst providing some insight, we would ideally have a variable that would explain a farmer's level of understanding of the technology, rather than a binary observation of knowledge that the variety exists. Though, the demands to gather this data may prove insurmountable in many cases. By controlling for the factors that would perhaps determine a farmer's level of understanding, such as rice growing experience, knowledge of other varieties and extension agency support, a good approximation can be provided. As the level of adoption increases, the use of adoption as a binary variable becomes less relevant. Under such cases, we are more interested in the *intensity of adoption* – the percentage of rice area being farmed using NERICAs.

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Appendix - Derivation of Estimators:

Appendix 1: Inverse Propensity Score Weighting

This derivation follows Diagne and Demont (2007, p.204) and uses the propensity score in estimating treatment effects. Note the use of X_i to denote the determinants of adoption and Z_i to denote the determinants of exposure. From the fact that $y_i(0)=0$, we have: $y_i = D_i.y_i(1)$. Then taking conditional expectations and applying conditional independence:

$$E\left[y_i \mid X_i, Z_i\right] = E\left[D_i \mid X_i, Z_i\right] E\left[y_i(1) \mid X_i, Z_i\right] \quad \text{(A.1)}$$

Assuming that adoption is independent from Z_i, conditional on X_i, then $E\left[y_i(1) \mid X_i, Z_i\right] = E\left[y_i(1) \mid X_i\right]$, and that exposure is independent from X_i, conditional on Z_i, $E\left[D_i \mid X_i, Z_i\right] = E\left[D_i \mid Z_i\right]$. Replacing the probability of exposure with the propensity score, $p(Z_i)$, then the outcome given exposure and adoption covariates becomes:

$$E\left[y_i \mid X_i\right] = p(Z_i) E\left[y_i(1) \mid X_i\right] \quad \text{(A.2)}$$

Recalling that the conditional ATE is given by: $ATE(X_i) = E\left[y_i(1) - y_i(0) \mid X_i\right] = E\left[y_i(1) \mid X_i\right]$, ATE is then identified by taking the expectation over X_i: $ATE(X_i) = E\left[y_i \mid X_i\right] / p(Z_i)$:

$$ATE = E_x\left[E\left[y_i \mid X_i\right] / p(Z_i)\right] \quad \text{(A.3)}$$

Where, under conditional independence the right hand side is estimable using a sample analog to the numerator: $\hat{m}(x_i)$ (or simply y_i), and the propensity score for the denominator, $\hat{p}(x_i)$:

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n} \frac{\hat{m}(x_i)}{\hat{p}(z_i)} \quad \text{(A.4)}$$

Since $\hat{m}(x_i)$ and $\hat{p}(x_i)$ can be estimated for the whole sample, ATT and ATU can also be estimated by taking the sample average over the treated and untreated sub-samples. In this paper we use an OLS regression for the former and a probit model for the latter:

Appendix 2: Matching Estimator

Conditional mean independence means that $E\left[y_i(1)\mid X_i, D_i\right]=E\left[y_i(1)\mid X_i\right]$. This means that $E\left[y_i(1)\mid X_i, D_i=1\right]=E\left[y_i(1)\mid X_i, D=0\right]$. Using observations of adoption in the treatment group (those with knowledge of NERICAs) as the counterfactuals for those in the non-treatment group, where matching is on the basis of observable characteristics in X_i, can then identify ATE, ATT and ATU provided the overlap assumption holds (Imbens et al., 2004, p.294). In the case of nearest neighbour matching, individuals are matched to minimise the distance between the covariates, $d_M(i)$, for the opposite treatment. Formally, $d_M(i)$ is the real number satisfying:

$$\sum_{l:W_l=1-W_i} 1\left\{\left\|X_l - X_i\right\|_v < d_M(i)\right\} < M \quad \text{and} \quad \sum_{l:W_l=1-W_i} 1\left\{\left\|X_l - X_i\right\|_v \leq d_M(i)\right\} \geq M$$

Where $\|x\|_v=(xv'x)^{\frac{1}{2}}$ is the vector norm with positive definite v, and $\left\|X_j - X_i\right\|_v$ represents the distance between the vectors X_l and X_i, which are covariate vectors for opposing treatment groups. After matching the estimates of the potential outcomes are used to estimate:

$$AT\hat{E}^{NN}=\frac{1}{n}\sum_{i=1}^{n}\left\{\hat{y}_i(1)\right\}=\frac{1}{n}\sum_{i=1}^{n}(2W_i-1)\left\{1+K_{iM}\right\}y_i$$

Where K_{iM} is used to denote the number of times an individual is used as a match. In our analysis we use one nearest neighbour.

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[1] Agboh-Noameshi et al (2006)

[2] Adekambi et al (2006)

[3] Goldman and Smith (1995) and Holmén (2003)

[4] See Agboh-Noameshi et al (2006), Kijima et al (2006) and Adekambi et al (2006) for studies on NERICAs impact.

[5] Feder et al. (1985) define adoption as the decision to use and innovation in long-run equilibrium *given* full information about its potential.

[6] Skinner and Staiger (2004), Dimmer and Skuras (2004).

[7] Foster and Rosenzweig (1995).

[8] Feder et al (1985), p.263, suggest that high-yielding varieties tend to be scale-neutral.

[9] Unfortunately, data restrictions limit our ability to control for this.

[10] Asfaw and Admassie (2003), p.216.

[11] Ibid., p.217.

[12] The observed sample adoption rate and the exposed sample adoption rate are frequently used to estimate adoption rates.

[13] For example, the number of adopters in the sample, Na/N, (the number of adopters, divided by the total population) will give a biased estimation if knowledge is not universal.

[14] See Imbens and Wooldridge (2009) and Angrist and Pischke (2009) for a concise account of developments in modern treatment effect estimation literature.

[15] Treatment in this case is being exposed to the technology. We study the effect of a farmer being 'treated'.

[16] Imbens and Angrist (1994) p.467.

[17] Heckman (1996) p.336.

[18] Wooldridge (2002) p.607.

[19] Imbens and Wooldridge (2009) p.26.

[20] Lee (2005) p.43.

[21] Heckman and Vytlacil (2005) p.667.

[22] Lee (2005) p.51.

[23] Imbens and Wooldridge (2009) p.45.

[24] See Zorn (2005)

[25] Crump et al (2009) p.169; Imbens and Wooldridge (2009) p.46; Angrist and Pischke (2009) p.89-90; present results exhibiting a greater degree of overlap between the covariates after adjusting the probability bounds to this recommended level.

[26] Angrist and Pischke (2009) p.90.

[27] Yet, this should not be to the same degree as experienced by parametric models under quasi-complete separation.

[28] This remedial action cannot ensure that the variables are exogenous though, as we are unsure of when a farmer became exposed to NERICAs. Yet, the variables cannot be excluded as they are likely to be important in explaining exposure and adoption decisions.

[29] All estimated treatment effects are statistically significant from zero at a 1% confidence level. '95% CI' refers to the lower and upper bounds of a 95% confidence interval. 'Estimator A' refers to the IPSW estimator, 'Estimator B' to the matching estimator. The outcome variable is adoption, the treatment is knowledge of NERICA. Results are rounder to three decimal places.

[30] Self-selection into treatment and via social networks are likely to attract a farmer who is more likely to adopt. Active targeting from extension services can be argued to select those with a lower or higher probability of adoption.

[31] There is no reason to suggest that this would be those with a higher propensity of adoption. Indeed, those targeted could be the isolated, rural poor, with little probability of exposure, but with large gains once adopted.

[32] For the case of NERICA impact, adherence to the conditional independence assumption is likely to provide difficulties, as many directly unobservable variables are likely to determine its impact, such as farm management techniques and pest impact etc. Scope to accurately study impact is therefore likely to require an instrumental variables approach, yet a randomised instrument may prove difficult to identify.

[33] National Agricultural Research Institute

[34] Department of Agricultural Services

[35] *=statistically significant from zero at 10%, **=5%, ***=1%. Bracketed number refers to the standard error of each parameter. Empty cells indicate this covariate wasn't used to determine the independent variable.

[36] *=statistically significant from zero at 10%, **=5%, ***=1%. Bracketed number refers to the standard error of each parameter. Empty cells indicate this covariate wasn't used to determine the independent variable, as theory suggests it would have no effect. For example, free seeds from an institution should not influence a farmer's exposure to NERICA – any effect would be picked up through the influence of extension activities and contact with institutions. SG2000 was ceased its activities before NERICA was available, thus it is reasonable to hypothesise that farmer contact with it can affect exposure, but not adoption.

[37] Camara et al (undated) p.32; Glenna et al (undated) p.7; report difficulties in threshing NERICA, which is traditionally done by females.

[38] *=statistically significant from zero at 10%, **=5%, ***=1%. Bracketed number refers to the standard error of each parameter. Empty cells indicate this covariate wasn't used to determine the independent variable.