31

29

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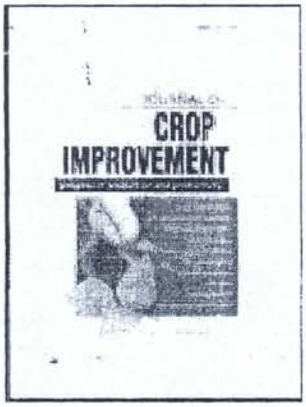

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Productivity Impact Differential of Improved Rice Technology Adoption Among Rice Farming Households in Nigeria

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391

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Productivity Impact Differential of Improved Rice Technology Adoption Among Rice Farming Households in Nigeria

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The contribution of technological change to agricultural productivity in developing countries has long been documented. It is believed that the adoption of new agricultural technologies, such as high-yielding varieties, could lead to significant increases in agricultural productivity and stimulate the transition from low-productivity, subsistence agriculture to a high-productivity agro-industrial economy. The article uses the local average treatment effect (LATE) to estimate the impact of adoption of improved rice varieties on rice farmers' productivity in the three major rice ecologies of Nigeria. A stratified random sampling was adopted by the study to select a sample of 500 rice farmers across ecologies. Findings of the analysis indicated that adoption of improved varieties helped raise farmers' area harvested and yield per hectare, respectively, by 0.39 hectare and 217.9 kg/ha for NERICA and 0.51 hectare and 210.4 kg/ha for other improved varieties, thereby increasing their productivity. In addition, NERICA varieties performed better than any other upland improved variety and the impact of its adoption on both area harvested and yield was greater among female rice farmers than among their male counterparts.

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392

Intervention programs to increase the dissemination of high-yielding rice varieties to areas with low productivity are, therefore, a reasonable policy instrument.

KEYWORDS Productivity, improved rice technologies, impact, local average treatment effect, Nigeria

INTRODUCTION

The contribution of technological change to agricultural productivity in developing countries has long been documented. Yet the distributional effect of technological change still provokes an interesting debate of international interests in both academic and policy circles. The debate on the distributional effect of technological change in the policy circle emerged following the success of the Green Revolution in Asia. Critics of the Green Revolution argued that the gain in production from technological change was offset by the loss in equity because small farmers were unable to use modern varieties efficiently. However, this argument proved to be wrong when empirical studies provided evidence that both small and large farms achieved approximately equal gains in efficiency (Ruttan 2002; Mendola 2007). In addition, agricultural growth is essential for fostering economic development and feeding growing populations in most of the less developed countries. However, because area expansion and irrigation have already become a minimal source of output growth on a world scale, agricultural growth will depend more and more on yield-enhancing technological change (Datt & Ravallion 1996; Hossain 1989). It is believed the adoption of new agricultural technologies, such as the high-yielding varieties that kick-started the Green Revolution in Asia, could lead to significant increases in agricultural productivity in Africa and stimulate the transition from low-productivity, subsistence agriculture to a high-productivity agro-industrial economy (World Bank 2008).

Rice has become an important economic crop and the major staple food for millions of people in Sub-Saharan Africa in general and Nigeria in particular (AfricaRice 2006). In Nigeria, its demand has been increasing at a much faster rate than in other West African countries since the mid-1970s. For instance, during the 1960s, Nigeria had the lowest per-capita annual consumption of rice in the sub-region (average of 3 kg). Since then, Nigerian per capita consumption levels have grown significantly at 7.3% per annum. In the mid-1970s, rice consumption rose tremendously at about 10% per annum. Consequently, per capita consumption during the 1980s averaged 18 kg and reached 22 kg during 1995–1999. Despite the fact that Nigerian per capita consumption caught up with the rest of West Africa, the Nigerian

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393

consumption level is still lower than that of the rest of the sub-region (34 kg in 1995–1999) (Akande 2001; Okoruwa, Rahji, & Ajani 2007).

The growing trend in rice consumption is partly explained by rapid population growth (estimated at 2.6% per annum), increasing urbanization and the relative ease of preservation and cooking. The poorest urban households in Nigeria obtain 33% of their cereal-based calories from rice, and rice purchased represents a major component of cash expenditures on cereals (Akanji 1995; World Bank 1995). These trends have meant that rice is no longer a luxury food but has become a major source of calories for the urban poor (Akpokodje, Lançon, & Erenstein 2001).

In recent years, rice production has been expanding at the rate of 6% per annum in Nigeria, with 70% of the production increase being mainly because of land expansion and only 30% being attributed to an increase in productivity (Falusi 1997; Fagade 2000; Okoruwa, Rahji, & Ajani 2007; AfricaRice 2007, 2008). Despite the upward trends in international and domestic rice prices, domestic rice consumption is increasing at a rate of 8% per annum, surpassing the domestic rice production growth rate of 6% per annum (Akpokodje, Lançon, & Erenstein 2001). Notwithstanding, the demand for rice is growing faster than production in the country, thus making the country dependent on imported rice to meet the demand. The persistence of a demand and supply gap has been attributed to several factors, prominent among which is the fact that nearly half of Nigeria's 140 million people live below the poverty line (World Bank 2004; NBS 2008), together with the lack of high-yielding varieties with good grain qualities, competition with imported rice, and inadequate post-harvest processing. Other factors are land degradation and inadequate land preparation; unreliable and uneven rainfall distribution; problems of weeds, insect pests, diseases, and birds; and lack of training for key stakeholders.

To address these problems, the Africa Rice Center and its NARs partners have developed different types of improved rice varieties for the rainfed lowland, upland, and irrigated rice farming systems of Nigeria. Among these varieties was the New Rice for Africa (NERICA)[1] varieties, which were seen as a first step toward stabilization and sustainable intensification of Africa's fragile production of upland rice. It was reported (Jones et al. 1997; Dingkuhn et al. 1998; Audebert et al. 1998; Johnson et al. 1998; Dingkuhn et al. 1999; Wopereis et al. 2008) to offer new opportunities for rice farmers because of its unique characteristics, such as shorter duration (maturing between 30 and 50 days earlier than traditional varieties), higher yield, tolerance to major stresses, higher protein, and good taste compared with the traditional rice varieties. These varieties had been introduced in Nigerian rice farming system since 1999 through participatory varietal selection (PVS) and have been adopted alongside others improved rice varieties by Nigerian rice farmers. Arising from the aforementioned are the following questions, which constitute the main focus of this study: What is the actual impact of

394

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the adoption of these improved varieties on rice farmers' productivity? What is the productivity impact difference between the adoption of NERICA varieties and that of other improved varieties across rice farming systems? The remaining part of the paper is organized as follows: section two presents both the conceptual and analytical framework of the study, section three deals with the methodology, and sections four and five are concerned with results, discussion, and conclusions.

FRAMEWORK OF THE STUDY

The Livelihood Framework

The livelihood framework approach is based on evolving thinking about poverty reduction, the way the poor and vulnerable live their lives, and the importance of structural and institutional issues. It suggests development activities that are people-centered, responsive and participatory, multi-leveled, conducted in partnership with both the public and private sectors, dynamic, and sustainable. The framework recognizes that every household and community has resources on which to build and support individuals and the community to acquire assets needed for long-term well-being. It is an attractive model because it provides a simple but well-developed way of thinking about a complex issue. It is also attractive because it can be applied at various levels of detail as a broad conceptual framework or as a practical tool for designing programs and evaluation strategies. It organizes the factors that constrain or enhance livelihood opportunities and shows how they relate to one another. Furthermore, it aims to build on strengths and is more than an analytical framework.

This study, therefore, adopts the livelihood framework approach developed by the U.K. Department for International Development (DFID; 2001) and adjusted by Diagne et al. (2009) to track down how the introduction of improved rice technologies and their adoption would affect the livelihood of rice farmers in Nigeria. Like in every society, individual households in Nigeria are endowed with infrastructural (road, electricity, market, health centers, storage facilities, etc.), natural (land, water, wildlife, and biodiversity), human (skills, aptitudes, knowledge, experience, labor, and good health), financial, physical, and social capital (savings, credit, remittances, pensions, transport, shelter, water, energy, communications, networks, groups, trust, mutual understanding, shared values, and access to institutions) resources that constitute the resource constraint based on which they maximize their well-being. These resources are affected by exogenous factors, such as agro-climatic conditions (drought, rainfall, etc.), insect pests, and diseases that hinder households' and farmers' productivity.

Changes in technology used through the development of improved varieties that have improved characteristics (drought tolerance, high yield, weed competitiveness, etc.), such as the NERICA varietie, and their dissemination

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through the participatory varietal selection (PVS) process, affect rice farmers' perception, beliefs, expectations, and preferences toward different rice varieties and inputs used in production. This is because, based on the characteristics of the new variety and demonstrations through PVS, farmers believe that their adoption would increase their yield and productivity and therefore they anticipate high benefits. These constitute the farmers' "value formation," which, in turn, conditions their decisions relative to investment, crops and varietal choice, and resource allocation to various inputs (seed, land, labor, fertilizer, and others inputs).

Their decisions must change because the new variety may need different types of inputs compared with what they were using before. These would thereafter affect their consumption, marketing of harvested quantities of different crop varieties, savings, income-generation activities, and consumption of other food and non-food items. Household decisions and choice constitute the behavioral outcomes, which will finally affect their income and poverty level (welfare outcomes).

To assess the impact of improved technology adoption on productivity, the choice of the appropriate approach to use for identification and estimation of impact depends on how the treatment (i.e., the technology) is disseminated and received by the intended beneficiaries. In this study, the PVS used to disseminate NERICA and other improved varieties in Nigeria was implemented in only a few selected states and villages (Spencer et al. 2006). This means that the overall population of Nigerian rice farmers was not equally exposed to the new varieties (the instrument for the policy intervention was not randomly distributed). On the other hand, rice farmers exposed to the new variety had full control over their decision to adopt or not to adopt (i.e., the receipt of the treatment is endogenous). According to the impact assessment literature, the most plausible assumption to make in this case is that of selection on the unobservable (Imbens & Wooldridge 2009; Diagne et al. 2009). This is because farmers decide to adopt improved varieties based on the anticipated benefit they would derive by adopting them; this anticipated benefit cannot be observed. Hence, to identify and estimate the impact of adoption of new varieties, we need an instrument that is independent of this unobserved, anticipated benefit and can affect outcomes (area harvested, yield per hectare) only through the act of adoption.

Analytical Framework

The Local Average Treatment Effect (LATE)

There is an expanding theoretical and empirical literature on models where the impacts of discrete (usually binary) treatments are heterogeneous in the population (See Roy 1951; Bjorklund & Moffitt 1987; Imbens & Angrist 1994; Heckman & Smith 1997; Card 2001; Heckman & Vytlacil 2005, 2007a,b).

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Under the potential outcome framework developed by Rubin (1974), each farm household has *ex-ante* two potential outcomes: an outcome when adopting a new variety (NV) that we denote by y_1, and an outcome when not adopting a new variety that we denote by y_0. If we let the binary outcome variable d stand for NV adoption status, with $d = 1$ meaning adoption and $d = 0$ non-adoption, we can write the *observed* outcome y of any farm household as a function of the two potential outcomes:

$$y = dy_1 + (1 - d)y_0. \tag{1}$$

For any household, the causal effect of the adoption on its observed outcome y is simply the difference between its two potential outcomes ($y_1 - y_0$). But, because the realizations of the two potential outcomes are mutually exclusive for any household (i.e., only one of the two can be observed *ex-post*), it is impossible to measure the individual effect of adoption on any given household. However, one can estimate the mean effect of adoption on a population of households. Such a population parameter is called the average treatment effect (ATE) in the literature (Imbens & Wooldridge 2009). One can also estimate the mean effect of adoption on the sub-population of adopters—$E(y_1 - y_0 | d = 1)$—which is called the average treatment effect on the *treated* and is usually denoted by ATT. The average treatment effect on the *untreated*—$E(y_1 - y_0 \mid d = 0)$—denoted by ATU is another population parameter that can be defined and estimated. Several methods have been proposed in the statistical and econometric literature to remove (or at least minimize) the effects of overt bias (caused by selection on observables) and hidden biases (caused by selection on unobservables), and deal with the problem of non-compliance or endogenous treatment variable. The methods can be classified under two broad categories based on the types of assumptions they require to arrive at consistent estimators of causal effects (see Imbens 2004; Imbens & Wooldridge 2009).

First, there are the methods designed to remove overt bias only. These are based on the 'ignorability' or conditional independence assumption (Rubin 1974; Rosenbaum & Rubin 1983), which postulates the existence of a set of observed covariates $\boldsymbol{x}$, which, when controlled, render the treatment status d independent of the two potential outcomes, y_1 and y_0, and has been widely used in the literature (Imbens & Wooldridge 2009). The estimators using the conditional independence assumption are either a pure parametric regression-based method, where the covariates possibly interact with treatment status variable to account for heterogeneous responses, or they are based on a two-stage estimation procedure where the conditional probability of treatment $P(d = 1| x) \equiv P(x)$ (called the *propensity score)*, is estimated in the first stage, and the ATE, ATT, and ATU are estimated in the second stage by parametric regression-based methods or by non-parametric methods. The latter include various matching method estimators, such as

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397

those used by Rosenbaum and Rubin (1985), Dehejia and Wahba (1999), Rosenbaum (2002), and Abadie and Imbens (2002, 2006). In this paper, the conditional independence-based estimators of ATE, ATT, and ATU that were used are the inverse propensity score-weighing estimators (IPSW), which are given by the following formulae (Imbens 2004; Lee 2005; Hirano et al. 2000; Hirano, Imbens, & Ridder 2003):

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)\left(1-\hat{p}(x_i)\right)} \tag{2}$$

$$A\hat{T}T = \frac{1}{n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\left(1-\hat{p}(x_i)\right)} \tag{3}$$

$$A\hat{T}U = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)} \tag{4}$$

where n is the sample size, $n_1 = \sum_{i=1}^{n} d_i$ is the number of treated (i.e., the number of NV adopters), and $\hat{p}(x_i)$ is a consistent estimate of the propensity score evaluated at $\boldsymbol{x}$. We use a probit specification to estimate the propensity score.

Secondly, there are instrumental variable (IV)-based methods (Imbens & Angrist 1994; Heckman & Robb 1995; Heckman & Vytlacil 1999, 2005; Manski & Pepper 2000; Abadie 2003; Imbens 2004) that are designed to remove both overt and hidden biases and deal with the problem of endogenous treatment. The IV-based methods assume the existence of at least one variable, an instrument called $\boldsymbol{z}$, that explains treatment status but is redundant in explaining the outcomes y_1 and y_0 once the effects of the covariates $\boldsymbol{x}$ are controlled. Different IV-based estimators are available, depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities. Other recent papers on semi-parametric and non-parametric models with non-separable error terms and an endogenous, possibly continuous, covariate, include papers using quantile instrumental variable methods, such as Chernozhukov and Hansen (2005) and Chernozhukov, Imbens, & Newey (2006), and papers using a control function technique, such as Imbens and Newey (2002), Blundell and Powell (2004), Altonji and Matzkin (2005), and Chesher (2003, 2007). In this study, we propose to use two instrumental variable (IV)-based estimators to estimate the LATE of adoption of NV on productivity, income, and poverty of Nigerian rice farmers (Imbens & Angrist 1994). The first one is the simple non-parametric Wald estimator proposed by Imbens and Angrist (1994), which requires only the observed outcome variable y, the treatment status variable d, and an instrument z. The second IV-based estimator is Abadie's (2003) generalization of the LATE estimator of Imbens and Angrist

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(1994) to cases where the instrument z is not totally independent of the potential outcomes y_1 and y_0, but will become so conditional on x, a vector of covariates that determines the observed outcome y.

Following the LATE estimator of Imbens and Angrist (1994) and that of Abidie (2003), we note that a farmer's exposure status to the NV varieties (i.e., his awareness of the existence of the NV varieties) is a 'natural' instrument for the NV adoption status variable (the treatment variable here). First, one cannot adopt a NV variety without being aware of it, and we do observe some farmers adopting NV (i.e., awareness does cause adoption). Secondly, it is natural to assume that exposure to NV affects the overall household productivity outcome indicators only through adoption (i.e., the mere awareness of the existence of a NV variety without adopting it does not affect the productivity outcome indicators of a farmer). Hence, the two requirements for the NV exposure status variable to be a valid instrument for the NV adoption status variable are met.[2] Now, let z be a binary outcome variable taking the value 1 when a farmer is exposed to the NV and the value 0 otherwise. Let d_1 and d_0 be the binary variables designating the two potential adoption statuses of the farmer with and without exposure to the NV varieties, respectively (with 1 indicating adoption and 0 otherwise).

Because one cannot adopt a NV variety without being exposed to it, we have $d_0 = 0$ for all farmers, and the *observed* adoption outcome is given by $d = zd_1$. Thus, the sub-population of potential adopters is described by the condition $d_1 = 1$, and that of actual adopters is described by the condition $d = 1$ (which is equivalent to the condition $z = 1$ and $d_1 = 1$). Now, if we assume that z is independent of the potential outcomes d_1, y_1, and y_0 (an assumption equivalent to assuming that exposure to NV is random in the population), then the mean impact of NV adoption on the poverty outcome of the sub-population of NV potential adopters (i.e., the LATE) is given by:

$$\begin{aligned} E\left(y_1 - y_0 | d_1 = 1\right) = LATE &= \frac{\operatorname{cov}(y, z)}{\operatorname{cov}(d, z)} \\ &= \frac{E\left(y \,|z = 1\right) - E\left(y \,|z = 0\right)}{E(d \,|z = 1) - E(d \,|z = 0)} \\ &= \frac{E\left[y_i \cdot (z - E[z_i])\right]}{E\left[d_i \cdot (z - E[z_i])\right]}, \end{aligned} \tag{5}$$

which is the well-known Wald estimator that can be estimated using two-stage least squares (Imbens & Angrist 1994; Imbens & Rubin 1997a; Lee 2005). For applications using parametric models with covariate, see Hirano et al. (2000) and Mealli et al. (2004). Moreover, it has been shown that, under the same assumptions, the entire marginal distributions of potential outcomes are identified for compliers (Imbens & Rubin 1997b; Abadie 2003).

399

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In particular, Abadie (2003) shows that if those assumptions[3] hold in the absence of covariates:

$$E\left(y_1 \mid d_1 > d_0\right) = \frac{E\left(y \cdot d \mid z = 1\right) - E\left(y \cdot d \mid z = 0\right)}{E\left(d \mid z = 1\right) - E\left(d \mid z = 0\right)}$$

$$E\left(y_0 \mid d_1 > d_0\right) = \frac{E\left(y \cdot (1-d) \mid z = 1\right) - E\left(y \cdot (1-d) \mid z = 0\right)}{E\left((1-d) \mid z = 1\right) - E\left((1-d) \mid z = 0\right)}$$

These equations identify average treatment responses for compliers.

The assumption that exposure to the NV varieties is random in the population is, however, unrealistic given the way the dissemination of NV took place in Nigeria (PVS). We therefore use Abadie's (2003) LATE estimator, which does not require the randomness assumption but instead requires the conditional independence assumption: the instrument z is independent of the potential outcomes d_1, y_1, and y_0, conditional on a vector of covariates $\boldsymbol{x}$ determining the observed outcome y. With these assumptions, the following results can be shown to hold for the conditional mean outcome response function for potential adopters $f(x,d) \equiv E(y \mid x, d; d_1 = 1)$ and any function g of (y, x, d) (Abadie 2003; Lee 2005):

$$f(x,1) - f(x,0) = (y_1 - y_0 \mid x, d_1 = 1) \tag{6}$$

$$E\left(g(y,d,x) \mid d_1 = 1\right) = \frac{1}{P(d_1 = 1)} E\left(k \cdot g(y,d,x)\right) \tag{7}$$

where $k = 1 - \dfrac{z}{p\,(z = 1 \mid x)}(1-d)$ is a weight function that takes the value 1 for a potential adopter and a negative value otherwise. The function $f(x, d)$ is called a local average response function (LARF) by Abadie (2003). Estimation proceeds by a parameterization of the LARF $f(\theta; x, d) = E\left(y \mid x, d; d_1 = 1\right)$. Then, using equation (3) with $g\left(y, d, x\right) = \left(y - f\left(\theta; x, d\right)\right)^2$, the parameter θ is estimated by a weighted least squares scheme that minimizes the sample analogue of $E[\kappa\ (y - f\ (\theta;\ x,\ d))^2]$. The conditional probability $P(z = 1|x)$ appearing in the weight κ is estimated by a probit model in a first stage. Abadie (2003) proves that the resulting estimator of θ is consistent and asymptotically normal. Once θ is estimated, equation (7) is used to recover the conditional mean treatment effect $E\left(y_1 - y_0 \mid x, d_1 = 1\right)$ as a function of x. The LATE is then obtained by averaging across x using equation (7). For example, with a simple linear function $f\,(\theta, d, x) = \alpha_0 + \alpha d + \beta x$ where $\theta = (\alpha_0, \alpha, \beta)$ then $E\left(y_1 - y_0 \mid x, d_1 = 1\right) = \alpha$. In this case, there is no need for averaging to obtain the LATE, which is here equal to α. Hence, a simple linear functional

400

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form for the local average response function with no interaction between d and x implies a constant treatment effect across the sub-population of potential adopters. In this paper, we postulate an exponential conditional mean response function with and without interaction to guarantee both the positivity of predicted outcomes (productivity) and heterogeneity of the treatment effect across the sub-population of potential NV adopters. Because exposure (i.e., awareness) is a necessary condition for adoption, it can be shown that the LATE for the sub-population of potential adopters (i.e., those with $d_1 = 1$) is the same as the LATE for the sub-population of *actual* adopters (i.e., those with $d = zd_1 = 1$).

As described above, the implicit specification of the LATE can be defined as follows:

$$Y_{iLATE} = f(\text{Adoption}, Si, Vi, Zi, Xi)$$

where Y_{iLATE} is the *ith* welfare component (area of rice harvested, yield per hectare); adoption is NERICA adoption status and determinant; S_i is a vector of covariates for the propensity score model; V_i is a vector of covariate for the instrument model; Z_i is a vector of covariates for the impacted outcome model (LARF); and X_i is the vector of covariates to be interacted with the adoption outcome variables. The detailed description of these variables is found in the appendix.

DATA AND DESCRIPTIVE STATISTICS

The data used in this study are based on a survey conducted in 2008/2009.[4] The survey covered the three rice ecologies in Nigeria where NV dissemination activities were being conducted: rainfed upland, rainfed lowland, and irrigated. The states of Osun, Niger, and Kano were selected randomly to represent, respectively, the three rice ecologies. Kano and Niger are located in the savannah zone, whereas Osun is located in the forest zone. A multistage-sampling approach was used to select the sample villages and farmers.

Six local government areas (LGAs) were randomly selected from each of the sampled states (with the exception of Kano with five LGAs). A total of 48 villages (16, 17, and 15 villages from Osun, Niger, and Kano states, respectively) were selected. These included villages where NVs had been introduced (called "NV villages") and the neighboring villages (5 to 15 kilometers away) where they yet to be introduced. The survey was carried out at two levels. At the village level, focus group discussions were conducted with selected farmers and the village head to obtain prior information about the village on its history, varieties grown, the state of infrastructure, constraints faced by rice farmers, and farm characteristics. Thereafter, the second level targeted individual farmers. On average, seven farmers were

401

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selected from each village in Osun and Kano, and 20 farmers from each village in Niger based on probability, in proportion to the number of rice farmers in the state. The total sample consisted of 500 farmers. Data on their socio/demographic characteristics, knowledge, access to seed, and adoption of NV, farm size, and returns were collected.

The distribution of socioeconomic/demographic characteristics of respondents in Table 1 reveals that the majority of respondents (93.1%), as well as those who adopted NERICA varieties (90%), were male. At the

TABLE 1 Household Socioeconomic Characteristics by Adoption Status

Characteristic	Other improved varieties (n = 380)	NERICA (n = 101)	Total (n = 481)
Gender			
Proportion of male farmers (%)	93.8	90.0	93.1
Proportion of female farmers (%)	6.2	10.0	6.9
Age (average)	45	49	47
Household size (average)	10	10	10
Farmer native of the village			
% born in the village	63.6	16.42	80.04
Number of years of residence in the village (average)	42	43	42
Access			
% having access to seed	2.0	88.2	27.0
% having access to credit	4.1	7.1	4.9
% having agriculture as major occupation	93.97	59.8	84.8
% having access to ICT	57.39	55.1	56.8
Distance to the nearest seed market (average)	3.72	5.75	4.26
Land area (ha) cultivated (average)	3.4	1.8	2.93
Number of improved varieties known by the farmer	1.7	1.4	1.6
Education and experience in rice farming			
% with no formal education	45.9	6.9	52.8
% with primary education	17.3	7.4	24.7
% with secondary education	13.1	6.4	19.53
% with post secondary school education	3.7	0.2	2.9
Proportion of farmers that receive vocational training (%)	5.8	5.8	11.6
Proportion of farmers with experience in lowland rice farming (%)	53.6	0.62	54.2
Proportion of farmers with experience in upland rice farming (%)	10.8	17.9	28.7
Proportion of farmers with experience in mangrove rice farming (%)	15.0	1.5	16.4
Institutional factors			
Proportion of farmers in contact with NCRI	1.7	11.0	12.68
Proportion of farmers in contact with ADPs	0.2	8.3	8.5

Source: AfricaRice/NCRI Baseline and priority setting survey 2009.

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402

time of the survey, the average age of the farmers was 47 years. The average household size among respondents (both adopters and non-adopters) was 10. Eighty percent of respondents were natives of their respective villages and had spent on average about 42 years in their villages. Most of the respondents (84.8%) stated agriculture as their major occupation, had an average cultivated land area of 2.91 ha, and were aware of an average of 1.6 improved varieties of rice. About 30.7% of farmers were aware of at least one NERICA variety, whereas 25.5% of them had access to its seed. Only 4.9% of the total sample had access to credit. The majority of both NERICA adopters (52.2%) and adopters of other varieties (57.4%) had access to information communication technology (ICT).[5] Respondents walked an average of 4.3 km to reach the nearest seed market. The educational level of the heads of households was significantly different between NERICA and adopters of other new varieties. There was also a significant difference between adopters of NERICA varieties and those of other new varieties in attendance at vocational training, as well as in the type of experience in rice farming. Data on institutional characteristics were also collected and their description among NERICA adopters and other NV revealed that 12.7% of farmers have access to extension services provided by NCRI, while 8.5% of them have access to extension services provided by Agricultural Development Programmes (ADPs).

RESULTS AND DISCUSSION

Descriptive Analysis of the Impact of NV Adoption

The descriptive analysis of the impact of NV adoption relative to area cultivated, rice output, yield, and annual rice income between adopters of

TABLE 2 Descriptive Analysis of the Impact of NV Adoption

Characteristics	Other improved varieties (n = 380)	NERICA (n = 101)	Total (n = 481)	Difference test
Area cultivated (hectares)	3.68	2.82	3.50	0.85**
	(0.18)	(0.84)	(0.23)	(0.57)
Yield (kg/ha)	2075.72	2577.57	2181.10	−501.85**
	(160.53)	(180.62)	(132.62)	(325.14)
Rice output (kg)	2028.41	1360.01	1887.76	668.39**
	(134.08)	(92.62)	(108.32)	(264.27)
Annual income of the household (Naira)	153129.6	84379.29	138693.5	68750.32***
	(8267.34)	(8455.41)	(6884.49)	(16626.52)
Male farmers	155590.2	90840.46	64749.75	64749.75***
	(8580.42)	(9160.71)	(7187.26)	(17599.78)
Female farmers	122196.4	31515.15	96619.66	90681.28*
	(30824.97)	(11832.62)	(23214.63)	(50110.2)

Source: AfricaRice/NCRI base line and priority setting survey 2009.

403

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NERICA and other improved varieties is given in Table 2. There was a significant difference in the area of land cultivated. The average area cultivated by farmers was 3.5 ha, whereas the difference test showed that the area cultivated by adopters of other improved adopters was significantly greater than that of NERICAs' adopters. The differences between NERICA and other NV adopters suggested a positive correlation between adoption and land asset ownership, with adoption being higher among larger farmers compared to landless and smaller farmers. Given that farm income remains a major source of income in rural Nigeria, allocation of land is, in turn, one of the important determinants of household income and, hence, expenditure levels.

The average land productivity was about 2.2 tons per hectare in the pooled data. This varied substantially between NERICA and other NV adopters. The results indicated that NERICA had the highest productivity compared to other NV adopters, as the yield was 2.1 and 2.6 tons per hectare for other NV adopters and NERICA adopters, respectively. However, the high yields from NERICA among their adopters could also be a result of other factors that were not related to NERICA adoption (such as good rainfall, use of fertilizer, etc.), and this pointed to the need to control such factors to establish the causal effect of NV adoption on productivity.

The Impact of NV Adoption on Area Harvested and Yield

The effect of adoption of improved varieties on income of the households was estimated with the LATE model. The LATE estimation was done for each of the outcome variables of interest (area cultivated for rice, yield, and gross income) using the two different estimation methods proposed by Imbens and Angrist (1994) and Abadie (2003). The LARF estimation required in Abadie's method uses as explanatory variables (in addition to the NV adoption status variable) a set of household and institutional variables such as the demographic characteristics, socio-economic characteristics, and the household's access to markets and institutions. The adoption status dummy variable was interacted with some of the covariates x to account for the heterogeneous impact. An exponential LARF was also estimated (using a nonlinear weighted least squares procedure) to avoid having some of the predicted outcomes be negative.

In Table 3 is given the impact of NV adoption on area harvested and yield. The adoption of improved rice varieties exerted a positive and significant impact on both the area harvested and the level of output per hectare by rice-farming households in Nigeria. Specifically, the LATE estimates suggested that NERICA adoption significantly increased the area harvested (by about 0.39 ha) and the output per hectare (by 217.94kg/ha); whereas the adoption of other new varieties positively increased area harvested (by 0.51 ha) and yield per hectare (by 210.37 kg/ha). These were interpreted as the average change in area harvested and yield, which were attributed to

404

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TABLE 3 Impact of NERICA Adoption on Area Cultivated and Yield

	Area of rice planted (hectare)		Yield (kg/ha)	
	NERICA	Other improved varieties	NERICA	Other improved varieties
LATE	0.39**	0.51	217.94***	210.37
	(0.87)	(0.27)	(000)	(358.68)
Male	0.17	0.68	187.51	328.41
	(0.10)	(0.28)	(323.79)	(367.76)
Female	0.92	0.43	4172.20***	–
	(0.82)	(0.82)	(1122.10)	
Impact Across Ecologies and Gender				
Upland	0.98	0.68	748.75	270.88
	(0.31)	(0.29)	(455.89)	(382.30)
Male	0.65	0.85	378.81	390.45
	(0.31)	(0.29)	(495.90)	(391.12)
Female	1.15	0.28	4841.37	–
	(0.51)	(0.82)	(1821.60)	
Lowland	0.21	0.40	222.59	344.63
	(0.32)	(0.56)	(308.34)	(727.61)
Male	–	0.05	104.9	241.58
		(0.65)	(320.60)	(855.53)
Female	0.33	1.22	3941.12	585.07
	(0.33)	(0.97)	(919.90)	(1263.09)
Irrigated	0.38	0.58	392.79	36.36
	(0.42)	(0.88)	(717.51)	(1149.23)
Male	0.14	0.58	392.79	36.37
	(0.23)	(0.88)	(717.51)	(1149.24)
Female	–	–	–	–

The figures in parentheses represent the robust standard error of the coefficients.

a change in technological status. In addition, the impact of NERICA adoption on both area harvested and yield was greater among female rice farmers than among male farmers. However, the reverse was the case for the adoption of other improved varieties as the impact was higher for male than for female farmers. This showed that NERICA could be used to help female farmers increase their productivity and therefore their income. NERICA varieties performed better than other upland varieties in the upland ecology as its adoption increased the area harvested (by 0.98 ha) and the yield (by 748.75 kg/ha) against 0.68 hectare and 270.88 kg/ha for other improved varieties. In contrast, NERICA varieties performed poorly in lowland and irrigated ecologies than the specific varieties of these ecologies. This can be explained by the fact that the two NERICA varieties considered in this study were upland NERICA and as such might not be suitable for other ecologies (lowland and irrigated).

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405

When compared with other studies, the impact on yield was smaller here than in the one conducted by Diagne (2006) for Cote d'Ivoire and Agboh-Noameshie, Kinkingninhoun, and Diagne (2007) for Benin. Furthermore, both studies showed that the impacts of NERICA adoption were higher for women than for men, which is also confirmed in this study. In addition, this is an answer to Orr et al.'s (2008) critiques on the performance of NERICA varieties compared to other improved varieties.

CONCLUSIONS AND RECOMMENDATIONS

In this paper, we examined the impact of the adoption of different rice improved varieties on household productivity in three major rice ecologies of Nigeria. Given the non-experimental nature of the data used in the analysis, associated with the biases and non-compliance behavior of some farmers, a local average treatment effect model was used. In addition, the local average response function was used to account for other factors that could have affected our outcomes. The results suggested the presence of bias in the distribution of covariates between groups of new variety adopters and non-adopters, indicating that accounting for selection bias was a significant issue.

Findings of the analysis indicated that adoption of improved varieties helped raise farmers' area harvested and yield per hectare, thereby increasing their productivity. In addition, the impact of NERICA adoption on both harvested area and yield was greater among female rice farmers than their counterpart male farmers. However, it is noteworthy to mention that the results from this study, as well as observations from other studies, such as Bellon and Risopoulos (2001), Diagne et al. (2009), and Javier and Awudu, (2010), showed that farmers generally continued to use the traditional rice varieties alongside the improved ones. This suggested that intervention programs to help extend the high-yielding rice varieties to areas where their productivity is high are therefore reasonable policy instruments to raise productivity in these areas, although complementary measures are needed.[6]

NOTES

1. Others improved varieties released at the same time with NERICA were FARO 53 and FARO 54.

2. The usual third requirement that the instrument be "uncorrelated with the unobserved error term" made in classical IV can be weakened by the Abadie (2003) generalization of the LATE identification estimation through the local average response function (LARF).

3. (i) Independence of the instrument: Conditional on X, the random vector (Y00; Y01; Y10; Y11; D0; D1) is independent of Z; (ii) exclusion of the instrument: $P(Y1d = Y0d|x) = 1 \textit{ for } d \in \{0, 1\}$; (iii) first stage: $0 < P(Z = 1|x) < 1 \textit{ and } P(d1 = 1|x) > P(d0 = 1|X)$; (iv) monotonicity: $P(d1 \geq d0|x) = 1$.

4. The first survey was carried out from December 2008 to February 2009, while the second survey, which collected data on household expenditure, was carried out during the second half of 2009.

406

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5. ICT was measure by access to new technologies for communication (radio, television, and mobile telephone).

6. This is introduced in the model to test for the linearity of age with adoption and access to NV seed.

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410

APPENDIX

Description of Variables Used for Impact Assessment

The variables used for the impact assessment model are divided in four groups. These include a group for propensity score, for the impacted outcomes, for interaction with the outcome variables, and a group for the instrument model.

Covariates for propensity score

Nknowdummy = 1 if the farmer is aware of at least one NV variety;
Seedacc dummy = 1 if the farmer has access to at least one NV variety seed;
Secondary education dummy =1 if the farmer has secondary education level, 0 otherwise;
Lowland dummy = 1 if the farmer practiced lowland farming system;
Upland dummy = 1 if the farmer practiced upland farming system;
Extension = 1 if the farmer has contact with extension officers;
Number of years of residence in the village;
Number of people leaving in the household;
Farnatv = 1 if the farmer is native of the village;
Maledummy = 1 if the farmer is a male;
Farmdummy = 1 if primary occupation is farming;
Voctrain = 1 if had vocational training;
Age of the household head in year;
Age squared[6];
Number of years of experience in lowland system;
Number of years of experience in upland system;
ICT = 1 if the farmer has access to radio, television or mobile phone;
Ncridum = 1 if the farmer has contact with NCRI officers;
Number of local rice varieties known by the farmer;
Distance to the nearest seed market in kilometer.

Covariates for the impacted outcomes

Age of the household head (years);
Maledummy = 1 if the farmer is a male;
Years of formal education (years);
Number of years spent in upland rice (years); and
Number of people leaving in the household.

Covariates to be interacted with the outcome variables

Age of the household head (years);
Maledummy = 1 if the farmer is a male;

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411

Extension = 1 if the farmer has contact with extension officers;
Years of formal education (in years);
Number of years spent in upland rice system (years); and
Number of people leaving in the household.

Covariates for the instrument model

Years of formal education (in years);
Number of years spent in upland rice system (year);
Osun State dummy (1 if from Osun state, 0 otherwise);
Niger State dummy (1 if from Niger state, 0 otherwise);
Number of years of residence in the village (year);
Number of people leaving in the household;
Farnatv = 1 if the farmer is native of the village;
Maledummy = 1 if the farmer is a male;
Extension = 1 if the farmer has contact with extension officers;
Farmdummy = 1 if primary occupation is farming;
Voctrain = 1 if had vocational training;
Age of the household head (years); and
Number of improved and local rice varieties known by the farmer.

All the estimations were done in Stata using the Stata add-on adoption-impact command developed by Diagne (2007) to automate the estimation of LATE models and related statistical inference procedures. The impact command is a Stata add-on command that works like standard Stata regression commands. Like the adoption command, 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, LATE Wald, the Abadie's LATE, and the local average response function (LARF).

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412