Impact of Adoption of Improved Rice Varieties on Income and Poverty Reduction among Rice Farmers in Cameroon

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Abstract

This study used the instrumental variables (IV)-based estimators to assess the impact of adoption of Improved Rice Varieties (IRV) on income and poverty among rice farming household in Cameroon. The key findings reveal a robust positive and significant impact on farm household income and poverty alleviation.

Keywords: program assessment, farming households, local average treatment effect

1. Introduction

Agriculture remains crucial for pro-poor economic growth in most African countries, as rural areas support 70-80% of the total population. More than in any other sector, improvements in agricultural performance have the potential to increase rural incomes and purchasing power for large numbers of people to lift them out of poverty (NEPAD, 2002; Wiggins, 2006). The main goal of agriculture research in Sub-Sahara African (SSA) is the development and dissemination of agricultural technologies targeted to poor farmers to contribute to poverty reduction and food security through the increase of rice farmers' productivity and income. The major achievement of rice research in SSA has been the development of high yielding modern varieties.

To contribute in achieving that purpose, improved rice varieties (IRV) and post-harvest technologies were developed by IRAD-Cameroon in collaboration with its partners (namely Africa Rice Center), and were disseminated in the country.

The present study aims to evaluate the impact of the adoption of these improved rice varieties on farmers' income and poverty status in Cameroon. This paper will first present a brief description of the methodological framework, the main results and then, gives some suggestions for improving rice farmers' welfare.

2. Literature overview

There is a rapidly growing literature evaluating the impact of anti- poverty programs in using experimental and non-experimental methods that deal appropriately with the self-selection problems (Ravallion, 2006; Todd, 2006). However, few of these studies have focused on assessing the impact of technology adoption on rural poverty. Notable exceptions include a study by Mendola (2006) on the impact of technology adoption on poverty in Bangladesh who uses the propensity-score matching (PSM) method to deal with the self-selection bias problem and estimates the *average treatment effect (ATE)* of adoption of high yielding rice varieties on income. However, by only controlling for the *observable* covariates that are partly responsible for the farmer self-selection into the adoption state the PSM only removes the part of the selection bias called "overt bias" (Lee, 2005; Rosenbaum, 2002). PSM cannot remove what is called "*hidden bias*" which is caused by the *unobservable* covariates that may also affect the farmer self-selection into the adoption state and the outcomes indicators (Heckman and Vytlacil, 2005; Rosenbaum, 2002).

Furthermore, when treatment is endogenous (as in the adoption case), we are faced with the *noncompliance* problem whereby subjects may not stick to their assigned groups even if assignment to the treatment and controlled groups were to be done randomly as in controlled social experiments (Imbens and Rubin 1997; Heckman, 1996; Angrist et. al, 1996; Imbens and Angrist, 1994). In the adoption context, *noncompliance* means that there are *never-takers* meaning farmers who will never adopt a technology even when they have free access to it. In this context, the ATE parameter estimated with the PSM method does not identify the causal effect of adoption. Instead, in the presence of non-compliance, ATE identifies what is defined in the evaluation literature as the *intention-to-treat effect* (ITT) which in the adoption context can be interpreted as the "supply-of-the-technology" effect (i.e. the impact of supplying a technology to farmers). The impact parameter that identifies the causal effect of adoption in the presence of *non-compliance* is the *local average treatment effect (LATE)* introduced by Imbens and Angrist (1994), which restrict the computation of the average treatment effect to the subpopulation of *"compliers*". In the adoption context the subpopulation of compliers correspond to that of potential adopters of the technology.

3. Analytical framework

Econometric framework

Under the potential outcome framework developed by Rubin (1974), each farm household has ex-ante two potential outcomes: an outcome when adopting a IRV variety that we denote by $y1$ and an outcome when not adopting a IRV variety that we denote by $y0$. Letting the binary outcome variable d stand for IRV 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: $y = dy1 + (1\text{-}d)y0$. For any household the causal effect of the adoption on its observed outcome y is simply the difference of its two potential outcomes: $y1$ - $y0$. 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: $E(y1\text{-}y0)$, where E is the mathematical expectation operator. Such a population parameter is called the average treatment effect (ATE) in the literature. One can also estimate the mean effect of adoption on the subpopulation of adopters: $E(y1\text{-}y0 \mid d=1)$, which is called the average treatment effect on the treated and is usually denoted by ATE1 (or ATT). The average treatment effect on the *untreated*: $E(y1\text{-}y0 \mid d=0)$ denoted by ATE0 is also another population parameter that can be defined and estimated.

The methods proposed to minimize the effects of overt and hidden biases and deal with the problem of *non-compliance* can be classified under two broad categories. (see Imbens 2004). First, there are the methods designed to remove overt bias only and which are based on the conditional independence assumption (Rubin, 1974) which postulates the existence of a set of observed covariates $\boldsymbol{x}$**,** which, when controlled for, renders the treatment status d independent of the two potential outcomes $y1$ and $y0$. The estimators using the conditional independence assumption are either a pure parametric regression-based method where the covariates are possibly interacted 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 $P(d = 1 \mid x) \equiv P(x)$, called the *propensity score*, is estimated in the first stage and ATE, ATE1 and ATE0 are estimated in the second stage by parametric regression-based methods or by non-parametric methods, which include various matching method estimators that include the ones used by Mendola (2006).

Second, there are the *instrumental variable* (IV) based methods (Imbens and Angrist, 1994; Abadie, 2003; Heckman and Vytlacil, 2005) which are designed to remove both overt and hidden biases and deal with the problem of endogenous treatment. The IV based methods assumes the existence of at least one variable z called *instrument* that explains treatment status but is redundant in explaining the outcomes $y1$ and $y0$, once the effects of the covariates $\boldsymbol{x}$ are controlled for. Different IV based estimators are available depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities. In this paper we use two IV-based estimators to estimate the LATE of adoption of IRV on household income. The first one is the simple non-parametric Wald estimator proposed by Imbens and Angrist, (1994) and which require only the observed outcome variable *y*, the treatment status variable *d* and an instrument *z*. The second IV estimator is Abadie's (2003) generalization of the LATE estimator of Imbens and Angrist (1994) to cases where the instrument *z* is not totally independent of the potential outcomes *y1* and *y0*; but will become so conditional on some vector of covariates ***x*** that determine the observed outcome *y*.

To give the expressions of the Imbens and Angrist's LATE estimator and that of Abadie (2003), we note that the exposure to the IRV status variable is a "natural" instrument for the adoption status variable (which is the treatment variable here). Indeed, firstly one cannot adopt an IRV without being exposed to it and we do observe some farmers adopting IRV (i.e. exposure does cause adoption). Second, it is natural to assume that exposure to IRV affects overall household expenditure/income only through adoption (i.e. the mere exposure to the IRV without adoption does not affect the expenditure/income of a farmer). Hence, the two requirements for the exposure status variable to be a valid instrument are met. Now, let *z* be a binary outcome variable taking the value 1 when a farmer is *exposed* to the IRV and the value 0 otherwise. Let *d1* and *d0* be the binary variables designating the two potential *adoption* outcomes status of the farmer with and without exposure to the IRV, respectively (with 1 indicating adoption and 0 otherwise). Because one cannot adopt a IRV without being exposed to it, we have *d0*=0 for all farmers and the *observed* adoption outcome is given by *d=zd1*. Thus, the subpopulation of potential adopters is described by the condition *d1*=1 and that of actual adopters is described by the condition *d*=1 (which is equivalent to the condition *z*=1 and *d1*=1). Now, if we assume that *z* is independent of the potential outcomes *d1*, *y1* and *y0* (an assumption equivalent to assuming that exposure to IRV is random in the population), then the mean impact of IRV adoption on the income of the subpopulation of IRV potential adopters is given by (Imbens and Angrist, 1994):

$$E(y_1 - y_0 \mid d_1 = 1) = LATE = \frac{\operatorname{cov}(y,z)}{\operatorname{cov}(d,z)} = \frac{E(y \mid z=1) - E(y \mid z=0)}{E(d \mid z=1) - E(d \mid z=0)} = \frac{E(y_i(z - E(z_i))}{E(d_i(z - E(z_i))}$$

which is the well known Wald estimator.

The assumption that exposure to the IRV is random in the population is unrealistic. We therefore use Abadie's LATE estimator which does not require this assumption but instead requires the much weaker conditional independence assumption: The instrument *z* is independent of the potential outcomes *d1*, *y1* and *y0* conditional on a vector of covariates ***x*** determining the observed outcome y. With these assumptions, the following results can be shown to hold for the conditional mean income response function for potential adopters

$$f(x,d) \equiv E(y \mid x, d; d_1 = 1)$$

and any for function g of (y, x, d) (see, Abadie, 2003; Lee 2005):

$$f(x,1) - f(x,0) = E(y_1 - y_0 \mid x, d_1 = 1)$$

$$E(g(y,x,d) \mid d_1 = 1) = \frac{1}{P(d_1 = 1)} E(k.g(y,d,x))$$

where, $k = 1 - \frac{z}{P(z=1 \mid x)}(1-d)$ 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(θ; x, d)= E(y | x, d; d1=1). The parameter θ is estimated by a weighted least squares scheme that minimizes the sample analogue of

$$E\left\{k(y - f(\theta; x, d))^2\right\}.$$

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.

In the estimation below, we postulate an exponential conditional mean income response function with and without interaction to guaranty both the positivity of predicted income and heterogeneity of the treatment effect across the subpopulation of *IRV* potential adopters. Because of the fact that exposure is a necessary condition for adoption, it can be shown that the LATE for the subpopulation of potential adopters (i.e. those with *d1*=1) is the same as the LATE for the subpopulation of actual adopters (i.e. those with d=zd1=1).

To consistently assess the impact solely due to the change in the technology, we use a latent-variable framework to estimate the marginal treatment effect-MTE (Heckman and al., 2003) and then, derive the LATE.

The poverty decomposition model

Foster, Greer and Thorbecke (1984) poverty model was used to decompose farmers into various poverty statuses. The headcount ratio, depth and severity of poverty were then calculated using the rural poverty line for Cameroon which is 269443 CFAs per capita per annum. The Foster, Greer and Thorbecke (FGT) index used is given by:

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^\alpha$$

4. Data used

Data were collected through a household survey conducted in 2009 by the Africa Rice Centre in collaboration with IRAD-Cameroon. The data collected pertain to the 2008 cropping season, and were collected from 1051 rice farmers in 120 villages. The data were collected on socio-economic characteristics, farmer knowledge and use of varieties, quantities of inputs and revenue from crops and non-farm activities.

5. Results and discussion

Impact on income and poverty using mean difference

The mean difference analysis of the impact of IRV adoption in terms of area cultivated, rice output, yield, income and poverty status between adopters and non-adopters of IRV varieties. As is evident from the table, the incidence of poverty was higher among non-IRV adopters (63.1%) than IRV adopters (52.0%). In addition, both the depth and severity of poverty were also higher among non-adopters than the adopters. All three poverty measures indicate that poverty was more prevalent and severe among non-adopters compared to adopters.

Table 1: Descriptive analysis of the impact of IRV adoption

Characteristics	**Non-adopters (n=173)**	**Adopters (n=878)**	**Total (n=1051)**	**Difference Test**
Area cultivated	0,4	0,56	0,53	-0,1619***
Yield	2,11	2,8	2,69	-0,69719***
Rice output	0,78	1,23	1,16	-0,4573***
Total income	270027,9	420014,9	395326,2	-149986,9**
Male farmers	243045,4	452980,8	422941,8	-209935,3*
Female farmers	298616,6	369085	355287	-70468,38*
Rice income	154753,5	193588,9	187196,4	-38835,41*
Male farmers	137422,8	193330,4	185330,7	-55907,6
Female farmers	103115,9	193988,4	189901,5	-20872,53*
Poverty measures				
Headcount ratio	63.1 (5.1)	52.0 (3.3)	57.55 (4.6)	0.11**
Poverty gap (depth)	26.2 (2.3)	20.4 (2.1)	23.3 (2.2)	5.8***
Poverty severity	13.09 (1.1)	10.44 (2.0)	11.765 (1.6)	26.5***

Caption: * significant at 10%; ** significant at 5% and *** significant at 1%

Source: AfricaRice/IRAD Base line survey 2009

Furthermore, the IRV adoption has had significant and positive impact on area cultivated, (+0.53 ha), rice output (+1.16 ton), yield (+2.69 ton/ha), total income (+395326 FCFA) and rice income (+187196 FCFA). However, the differences in observed mean outcomes between adopters and non-adopters cannot be attributed entirely to IRV adoption due to the problem of self-selection and non-compliance (Heckman and Vytlacil, 2005; Imbens and Angrist, 1994). The impact of the adoption of new agricultural technologies on poverty and income levels is discussed in the next section through a counterfactual econometric framework.

The impact on income and its determinants

The impact of improved technology adoption on household income of rice farmers' was estimated through the local average treatment effect (LATE). Results (see table 2 below) show that IRV adoption had a positive and significant effect on household income. Adoption of IRV increased the income of adopters by 7 085.99 CFA. The Abadie's LATE estimator of 84 611.06 CFA is significantly larger in magnitude than the Wald estimate of 7 085.99 CFA. The impact is significantly higher in households headed by female (120 082.70 CFA) than those headed by males (60928.37). Moreover, analysis across ecologies indicates that the impact was highest irrigated ecology (139 481 CFA) than other ecologies. In addition, adoption of IRV significantly increased the income of farmers within the poverty severity more than that of farmers within the poverty headcount and poverty gap. This finding is in line with the one gotten by Diagne et al. (2009) who find that the New Rice for Africa (NERICA) varieties adoption in Benin had the potential to reduce poverty significantly.

Table 2: The impact of IRV adoption on rice income

Parameters	LATE	LATE-Wald
ATE	84611.06***	7085.99**
ATE1		
ATE0		
Impact by gender		
Male	60928.37**	
Female	120082.70**	
Impact by ecology		
Lowland	64202.96*	
Irrigated	139481,23**	
Upland	75412.27*	
Impact by poverty status		
Headcount ratio (incidence)	69171.67**	
Poverty gap (depth)	52718.12***	
Poverty severity	72752.3***	

Source: AfricaRice/IRAD Base line survey 2009

The determinants of income as given by their local average response functions (LARF) were estimated and the results in Table 3 indicate that, apart from a change in technology used (IRV adoption), age, education level, area cultivated, the type of rice farming (upland) and the existence of market in the village significantly explain the change in farmers' income. A number of coefficients for the interacted terms were also statistically significant, thus confirming the heterogeneity of the impact of IRV adoption on household income. The coefficient (-0,317) for the gender of the head of household is negative and significant, indicating that male-headed households have less income than female headed households. The coefficients (8.016 and 0.002) of the household size and age are positive and significant at 5% level, showing that increase in any of these variables would lead to an increase in income.

Table 3: Determinants of farmers' rice income using Exponential LARF regression

Rice income	Coefficients	Std. Err.	t-Statistics
Adoption of IRV	11.943	0.379	31.48**
Sex	-0.317	0.217	0.8**
Age	0.002	0.000	4.56***
No formal education	-0.225	0.496	-0.46**
Size of household	8.016	0.105	0.1**
Area cultivated	6.223	2.918	2.14**
Age_adoption	-0.002	0.000	-4.53***
Size of household_adoption	-0.016	0.154	-0.11
Existence of market in the village_adoption	0.543	0.261	2.08**
Contact with extension services_adoption	0.503	0.296	-1.7*
Irrigated_ adoption	0.124	0.335	-0.37**
Upland_ adoption	0.663	0.241	2.76***
Area cultivated _ adoption	6.793	2.814	-2.41**
R-squared	0.1267		
Adj. R-squared	0.1143		
Wald test for the joint significance of all coefficients	362.86***		
Wald test for non-interacted terms	143.22***		

Caption: * significant at 10%; ** significant at 5% et *** significant at 1%

Source: AfricaRice/IRAD Base line survey 2009

The interaction terms for age and household size are negative and significant, suggesting that the impact of IRV adoption on households' rice income will be smaller among elderly farmers and larger households. However, the interaction terms of existence of market in the village and contact with extension services are positive and significant, suggesting that the impact of IRV adoption will be high for elderly farmers and those with large farm sizes.

6. Conclusions

This study examined the impact of adoption improved rice varieties on farmers' income and poverty status in Cameroon. A counterfactual outcome framework of modern evaluation theory is used to consistently estimate improved rice varieties adoption impact on household revenue. The study was undertaken to understand the pathways of the impact of technological progress in rice cultivation on the livelihood of the rural households, particularly of the poor. Overall, the findings indicate that the adoption of IRV has had a positive and significant effect on revenue thereby increasing their probability of escaping poverty. Moreover, the impact is found to be higher among women than men and in other side, this impact is higher for irrigated system (139 481 FCFA) than other ecologies. These results suggest that adoption of improved rice varieties is associated with poverty reduction and that there is a great scope for reducing poverty by promoting the cultivation of improved rice varieties in Cameroon. This confirms the view that productivity-enhancing agricultural innovations can contribute to raising incomes of farm households, poverty alleviation, and food security in developing countries.

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