Improved Rice Technology Adoption and Household Welfare in Nigeria

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1. Introduction

Agriculture remains the base of Nigeria’s economy, employing over 60% of her labor force and contributes about 24.18% to GDP (CBN, 2016). The sector mainly consists of smallholder farmers who operate at subsistence level (WB, 2014) and has the highest poverty incidence in the country (Philip et al., 2009). In Nigeria, food crop production has not maintained pace with population growth, resulting in rising food imports and declining levels of national food self-sufficiency (FAO). Rice is the most important food crop in Nigeria, as well as an important food security crop and an essential cash crop. Rice generates more income for Nigeria’s farmers in comparison to any other cash crop in the country. Nigeria is Africa’s leading consumer and producer of rice and simultaneously, the second-largest importer of rice globally. In 2013, Nigeria’s total annual demand for milled rice was put at approximately 5.3 million tons, while 3.1 million tons of rice (milled equivalent) was produced locally; a gap of approximately 2.2 million tons was imported (Ricepedia, 2013). Over a period, the government has initiated various agricultural development programs focusing on the importance of growth in agriculture as a path out of poverty particularly through increased productivity and commercialization among smallholder farmers. Improved quality seeds, fertilizers, and other inputs are occasionally distributed to smallholder farmers, the adoption of this improved varieties is critical for productivity gains and poverty reduction; however, the progress of these new technology adoptions by farmers is very slow, owing to the existence of several constraints that discourage farmers from adopting new technologies (Feder et al., 1985; Feder and Umali, \textsuperscript{1)*}

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Many researchers have investigated the reasons for the low adoption rate. Existing literatures note that age, credit, education, information availability, risk, risk attitude, time preference, and farm size affect the adoption decision of new technology (Feder et al., 1985; Foster and Rosenzweig, 2010). The welfare implications of technology adoption are also a continuing concern for many social scientists, the impact of modern rice varieties has received considerable attention (Feder and Umali, 1993). Although significantly complex, the relationship between the adoption of new technology and poverty reduction has been perceived as positive (Mekonnem, 2017; Sahu and Das, 2015; Bellon et al., 2006;Binswanger and Von Braun, 1991; Evenson and Gollin, 2003; Just and Zibberman, 1988; Mendola, 2007). Over time, statisticians and econometricians have formulated models and estimators to accurately evaluate the impact of technology adoption, popular amongst them is the propensity score matching (PSM) widely used. The “Endogenous Treatment Effect Model despite its advantages have not received so much attention. The treatment effect model is useful in producing improved estimates of an average treatment effect. The results of a Monte Carlo study comparing models ranked the treatment effect model first, among six other models, for providing excellent estimations of the average treatment under certain conditions (Guo and Fraser, 2015: p. 354).

The objectives of this study are as follows: Firstly, this study tries to examine the factors influencing farmers’ adoption decision of improved rice seed technology in the study area.

Secondly, this study tries to evaluate the welfare impact of adopting improved rice seed technology on farmers’ welfare in the study area.

To attain these objectives, this study employs the “Endogenous Treatment Effect Model”. The endogenous treatment effect model is one of the “Heckit” models developed to estimate the average treatment effect (ATE) and other parameters of a linear regression model augmented with an endogenous binary variable to correct for selection bias, while estimating treatment effectiveness. This model uses the probit model to estimate the selection equation.

The results of this paper add to existing evidence on the potential impact of agricultural technologies on the welfare of farm households. Firstly, to the best of my knowledge, this is the first time that the endogenous treatment effect estimation methodology is applied to an impact assessment study in Nigeria. Secondly, The Endogenous Treatment Effect Model despite its advantages is not widely used (Only one known case, Mekonnem, 2017) thus, this paper therefore contributes to the thin literature on impact assessment by the Endogenous Treatment Effect Methodology.

2. Data

The data used in this paper originates from a socio-economic and agricultural technology survey conducted by African Rice Center (AfricaRice) under the emergency rice initiative funded by the United States Agency for International Development in 2010. The data was collected through a multi-stage random sampling in Kano, Osun, and Niger states. Overall, 600 rice growing households that were randomly selected from various states participated in the survey.

In this study, adopters are classified as farmers who planted any of the improved rice varieties, irrespective of the area planted and non-adopters are those who did not cultivate any of the improved varieties in their farm. Literature shows that many adopters do not fully allocate their land to improved varieties as they also grow traditional varieties (Asfaw et al., 2012).

3. Analytical framework

(1) Adoption Decision

Suppose the choice of a given farm household is binary such that farmers choose to either adopt a given technology or not, the adoption decision-making process and impact of improved rice technology on farm household welfare can be modelled in an optimization framework. Given that farmers are risk neutral
and tend to optimize their utility by maximizing farm output as well as reducing poverty, we can evaluate the net welfare (\(G^*\)) associated with adoption and non-adoption of improved rice technology, denoted by \((U_{Ai})\) and \((U_{Ni})\), respectively. To the extent that only the adoption status is known to the researcher, but the household preferences like net welfare are known to only the farmer, the net welfare from rice technology adoption can be expressed with respect to a vector of household explanatory variables in a latent variable framework as

\[
G^*_i = BX_i + u_i \quad \text{(i)}
\]

\[
G^*_i = 1 \text{ if } G^*_i > 0 \text{ otherwise, } G_i = 0 \quad \text{(ii)}
\]

Where \(G\) is a binary indicator variable that equals 1, if a farmer uses an improved rice variety and zero otherwise, \(\beta\) is a vector of parameters to be estimated, \(X\) includes all the observable factors that may influence improved rice technology adoption decision such as household and farm-level characteristics. (see, Table 1), \(u\) is the error term with mean zero.

**Impact Evaluation and selection bias**

This study investigates the impact of improved rice technology adoption on farm household welfare. Following Asfaw et al. (2012) and Mekonnen (2017), this study relies on the per capita consumption expenditure of households as a measure of welfare. Household consumption expenditure reflects the effective consumption of households, and therefore provides information on food the security status and the wellbeing of households, it is a more reliable welfare indicator and less prone to measurement errors in comparison to total household income (Asfaw et al., 2012; De Janvry and Sadoulet, 2016: p. 205).

Given that this vector of outcome is a linear function of observed farm and household characteristics, the outcome variable can be expressed as

\[
Y_i = \alpha J_i + \eta G_i + e_i \quad \text{(ii)}
\]

where \(Y\) represents a vector of outcome variable (welfare – measured by household consumption expenditure); \(G\) as previously described in (i) is an indicator of household adoption status; \(J\) is a vector of observed farm and household characteristics; \(\alpha\) and \(\eta\) are vectors of parameters to be estimated; \(e\) is the error term.

In (ii), the impact of adoption on the outcome variable is measured by the estimates of the parameter \(\eta\). This approach however, may generate biased estimates because the decision of households towards technology use is not random or voluntary and may be based on individual self-selection in which case, the undeclared factors, \(e\), in (ii) tend to influence on \(u\) in (i).

This implies that the correlation coefficient of the error terms is not equal to zero, hence OLS tend to yield biased estimates. To cope with this selection bias problem, the PSM approach is commonly used. However, a major drawback of the PSM approach is that it only accounts for observables factors. To simultaneously estimate the determinants and impact of adoption, while accounting for both observable and unobservable factors considering the endogeneity of households’ adoption decision, the “Endogenous Treatment Effect Model” is employed following Mekonnen (2017).

**Endogenous treatment effect model**

The endogenous treatment effect model estimates the Average Treatment Effect (ATE) and other parameters of a linear regression model that also includes an endogenous binary-treatment variable. Estimation is by full information maximum likelihood.

This model is expressed in two sets of equations as follows (using (i) and (ii))

**Regression/Outcome equation:**

\[
Y_i = \alpha J_i + \eta G_i + e_i \quad \text{(ii)}
\]

**Selection equation:**

\[
G_i = BX_i + u_i \quad \text{(i)}
\]

\[
G_i = 1 \text{ if } G_i > 0 \text{ otherwise, } G_i = 0 \quad \text{(ii)}
\]

Where \(G\) is the dummy variable indicating the treatment condition (i.e. \(G_i=1\), if participant \(i\) is in the treatment condition, otherwise \(G_i=0\)) and \(Y\) is the outcome variable of the regression equation (observed
for both \( G_i = 1 \) and \( G_i = 0 \).

\[
Prob \ (G_i = 1 \mid X_i) = \Phi(X_i \beta)
\]

and

\[
Prob \ (G_i = 0 \mid X_i) = 1 - \Phi(X_i \beta)
\]

where \( \epsilon_i \) and \( u_i \) are bivariate normal with mean zero and covariance matrix \( \begin{bmatrix} \sigma^2 & \rho \sigma \\ \rho \sigma & 1 \end{bmatrix} \). Here \( \sigma^2 \) is the variance of the disturbance term \( \epsilon_i \), in \((ii)\), the variance of the error term \( u_i \), in \((i)\) is assumed to be 1 and \( \rho \sigma \) is the covariance of \( \epsilon_i \) and \( u_i \).

4. Estimation results and discussion

The summary statistics of variables considered in this study is summarized in Table 1, which describes the socio-economic characteristics of households in the study area. It indicates that approximately 62% of the sampled households adopted improved rice varieties. These farmers are on average about 45 years of age and have an average of 37 years of farming experience.

Table 2 presents the mean difference in certain indicators between adopters and non-adopters of improved rice seed. It shows that there is a significant difference in household characteristics and variables of interest amongst adopters and non-adopters of improved rice technology in the study area.

Table 3 shows the treatment effect model estimation results of both our regression/outcome equation and the selection equation.

The treatment effect model assumes that the correlation between the two error terms is non-zero and violation of these assumptions can lead to estimation bias. The likelihood ratio (LR), tests that \( p = 0 \). This ratio test, is a comparison of the joint likelihood of the independent probit model for the selection equation.

**Table 1. Summary statistics variables.**

| Variable     | Description                                      | Mean    | Std. Dev. |
|--------------|--------------------------------------------------|---------|-----------|
| Dependent Variables |                                                 |         |           |
| Y            | Per capita consumption expenditure (Nigerian Naira) | 34347.99 | 18226.89  |
| G            | Limited dependent Variable: 1 if Farmer used an improved rice variety. 0 otherwise. | 0.62    | 0.49      |
| Independent Variables |                                               |         |           |
| RiceYield    | Rice Yield (kilograms per hectare)               | 3271.07 | 2238.76   |
| Age          | Age of Household head                           | 45      | 8.62      |
| Age2         | Square of the age of Household head             | 2117    | 790       |
| HhSize       | Household size: Number of persons living in the household | 8      | 4.09      |
| Gender       | 1 if household head is male, 0 otherwise.       | 0.81    | 0.4       |
| Education    | Education level of farmer: 1 if farmer has formal education, 0. otherwise. | 0.68    | 0.47      |
| Frmsize      | Cultivated area of rice (hectare)               | 2.4     | 1.56      |
| AssetVar     | Asset Holding: 1 if farmer owns a home, 0 otherwise. | 0.86    | 0.35      |
| MemOfOrg     | Membership of Organization: 1 If farmer is a member of a farm organization, 0 otherwise. | 0.31    | 0.46      |
| Acredit      | 1 if farmer was able to obtain credit, 0 otherwise. | 0.23    | 0.42      |
| MainAct      | Main activity: 1 if farming is main occupation, 0 otherwise | 0.9     | 0.31      |
| FarmExp      | Years of farming experience                     | 37      | 11.32     |
| Training     | 1 if farmer has attended farm trainings, 0 otherwise. | 0.21    | 0.41      |
| Off-farmInc  | Off-farm Income (Nigerian Naira)                 | 91859.02| 118749.4  |
| Osun         | Dummy: 1 if farmer is located in Osun, 0 otherwise | 0.15    | 0.36      |
| Niger        | Dummy: 1 if farmer is located in Niger, 0 otherwise | 0.67    | 0.47      |
| Kano         | Dummy: 1 if farmer is located in Kano, 0 otherwise | 0.18    | 0.38      |

Source: African Rice field survey, 2010.
Table 2. Mean difference in certain indicators between adopters and non-adopters of improved rice seed technology.

| Variables          | All (N=563) | Adopters (N=348) | Non-adopters (N=215) | Difference | T-value |
|--------------------|-------------|------------------|----------------------|------------|---------|
| Consumption Expenditure | 34384 (768.17) | 35737.47 (1020.48) | 32098.99 (1134.28) | 3638.48 | 2.31** |
| Average Yield (Kg/Ha) | 3271.07 (94.35) | 3408.13 (122.47) | 3049.22 (146.57) | 358.9 | 1.85* |
| Household Size     | 8 (0.17) | 9 (0.23) | 7 (0.22) | 2 | 6.11*** |
| Off-farm Income (Nig Naira) | 91859.02 (5004.69) | 118834.4 (7351.22) | 48196.6 (400.08) | 70637.76 | 7.16*** |
| Asset Holding (House) | 0.86 (0.01) | 0.91 (0.02) | 0.78 (0.03) | 0.13 | 4.52*** |
| Education         | 0.683 (0.02) | 0.66 (0.03) | 0.72 (0.03) | −0.06 | 1.48NS |
| Membership of Org. | 0.312 (0.02) | 0.44 (0.03) | 0.1 (0.21) | 0.34 | 9.04*** |

Source: Calculated from African Rice field survey data, 2010.
Standard errors are in parenthesis.
***, ** and * indicate significance at the 1%, 5%, and 10% levels of probability, respectively and NS=not significant.

Table 3. Endogenous treatment effect estimation result

| Variables             | Outcome Equation, (ii) | Selection Equation, (i) |
|-----------------------|------------------------|------------------------|
|                       | $Y$                    | $G$                    |
|                       | Coefficient$^{1)}$     | $SE$                   | Coefficient$^{1)}$     | $SE$       |
| Age                   | −0.000838             | 0.0158                 | −0.183***             | 0.0558     |
| Age2                  | 8.61E-05              | 0.000168               | 0.00168***            | 0.000595   |
| ln(Household size)    | −0.687***             | 0.0484                 | 0.323**               | 0.148      |
| Primary Education     | 0.0523                 | 0.0583                 | 0.225NS               | 0.189      |
| Higher Education      | 0.248**               | 0.107                  | −0.237NS              | 0.350      |
| Gender                | 0.180***              | 0.0566                 | −0.382**              | 0.187      |
| ln (Farm Size)        | −0.0361               | 0.0247                 | 0.137*                | 0.0802     |
| Asset Holding         | 0.0718                | 0.0695                 | 0.475*                | 0.261      |
| Membership of Org.    |                       |                        | 0.706***              | 0.172      |
| Off Farm Income       | 4.63e-07**            | 1.93E-07               | 5.40e-06***           | 9.54E-07   |
| Main Activity         | 0.111                 | 0.0711                 | −0.121NS              | 0.223      |
| Farming Experience    | 0.0160***             | 0.00213                | 0.0249***             | 0.00729    |
| Training              | 0.148***              | 0.0572                 | 0.579**               | 0.23       |
| Osun (Location dummy) |                       |                        | 0.22NS                | 0.267      |
| Kano (Location dummy) |                       |                        | 1.527***              | 0.259      |
| $G$                   | 0.440***              | 0.0844                 |                       |            |
| Constant              | 10.20***              | 0.362                  | 2.526*                | 1.329      |
| Observations          | 563                   |                        | 563                   |            |

Rho: Coefficient: −0.6251, SE: 0.904.
Likelihood Ratio (LR) test of independent equations. (rho=0); chi2=23.89 Prob>chi2=0.0000

Source: Stata output, calculated from African Rice field survey data, 2010.
1) ***, ** and * indicates significance at the 1%, 5% and 10% levels of probability and NS=not significant.
and a regression model on the observed data against the treatment effect model likelihood. In this case, \( \chi^2 = 23.89 \) (\( p < 0.01 \)), we can therefore reject the null hypothesis and conclude that \( \rho \) (rho) is not equal to zero. This suggests that applying the treatment effect model is appropriate.

The endogenous treatment effect result (Table 3) shows that agricultural technology adoption positively affects the welfare of households. The coefficient of our treatment variable, \( G \) (0.44) in table 3 (column 2) is positive and statistically significant. Thus, the estimated ATE of the impact of adoption of improved rice technology on welfare is 0.44. The ATET is the same as the ATE in this case as the treatment indicator variable has not interacted with any of the outcome covariates, and the correlation and variance parameters are identical across the control and treatment groups. Hence, all things being equal, the households that choose to adopt improved rice varieties will have a 55.3\% (e^{0.44}) higher consumption expenditure in comparison to households who do not adopt improved rice seed technology. This result is consistent with existing studies (Mendola, 2007; Mulugeta and Hundie, 2012).

The direct effects of new agricultural technology on welfare are the productivity benefits enjoyed by the farmers adopting new technology. These benefits generally manifest themselves in the form of higher farm income. Due to data limitation and scope, this study didn’t empirically show the effects of improved rice technology on rice yield and income. However, previous research shows it to be positive. (Sahu and Das, 2015).

The major factors that significantly affect farmers’ technology adoption decisions are reported in column 2 (selection equation) of table 3. Age, household size, gender, farm size, asset holding, membership of organization, off-farm income, farm experience, and training were all statistically significant. The statistically significant and negative coefficient of age indicates that the older the farmer is, the less likely they are to adopt a new technology. Polson et. al., (1992) observed that younger household heads are more dynamic with regards to adoption of innovations.

Off-farm income (generally used as proxies for a households’ ability to invest in technology) is statistically significant with positive coefficients. As shown in table 1, most of the farmers are credit constrained; hence, off-farm income of households is important in financing farm operations.

The adoption decision of modern varieties is positively and significantly influenced by the proxy for asset holding (home ownership in this case). One plausible explanation is that ownership of these assets eases access of households to credit. The use of modern varieties requires larger cash outlays in comparison to ordinary seeds owing to the higher price and requirement of more inputs of fertilizers and pesticides to exploit the yield potential of the modern varieties. Hence, as most farmers possess insufficient accumulated savings, the availability of these assets enables them to gain the necessary capital to invest in technology. These results are similar to those in existing literatures.

The importance of extension has been highly recognized in the adoption of modern technologies. In this study, attendance by farmers at training sessions has a significant and positive impact on the adoption of modern varieties. According to Mariano et. al. (2012), access to such kind of capacity enhancement significantly increase the probability of improved seed adoption.

The importance of family labor (as proxied by household size) is reflected in this study. Modern varieties generally require more labor inputs; hence, labor shortages may prevent adoption. The positive and significant effect shows how family labor is important in the study area. Harris (1972) found that shortages of family labor explains non-adoption of modern varieties in India.

The effect of farm size on farmers’ decisions to use modern rice varieties is positively significant. Studies have shown that inadequate farm size impedes the adoption of certain types of innovations. Much of evidence indicates that the incidence of adoption of mod-
ern varieties is positively related to farm size (Binswanger et al., 1978).

Membership of organization is regarded as an important component of social capital (Awotide et al., 2016). It is expected to improve farmers’ access to appropriate information on modern varieties and their access to credit facility. As demonstrated in this study, the positive and significant results are in tandem with previous findings.

5. Summary, Conclusion & recommendation

Result of this study shows that improved rice technology adoption positively contributes towards the welfare of rural households in the study area.

The factors that influence farmers’ adoption decision include age of the household head, labor availability, farm size, asset holding and membership of farm organization, off-farm income, farming experience, and contact with extension. To improve productivity, food security, and welfare of smallholder farmers, policy priority should be geared toward improving access to credit and fund extension activities, such as training. Furthermore, farmers should be encouraged to join farmers’ organizations or cooperatives as these would ease their access to information on agricultural innovations, in addition to access to credit facility.

The results of this study offer evidence to the potential impact of agricultural technologies on crop productivity and welfare of households in Nigeria.

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