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Assessing the exposure and effect of adoption of improved rice varieties on the net rice income of Ghanaian farming households

Shamsudeen Abdulai

Department of Agricultural & Food Economics, Faculty of Agriculture, Food & Consumer Sciences, University for Development Studies, Tamale. e-mail: shamsudeen.abdulai@yahoo.com, ORCID ID: http://orcid.org/0000-0002-2303-8349

ABSTRACT

This study analysed the exposure and effect of adoption of improved rice varieties on household net rice income per hectare of 576 Ghanaian households for 2012/2013 cultivation season. Exposure to improved rice varieties was estimated to account for non-exposure bias, followed by the effect of adoption on net rice income for the exposed households using switching regression. Rice projects and agricultural input shops in communities increased exposure to improved rice varieties. Similarly, community participation in rice projects, being a model farmer, participation in block farming, agricultural extension, seeking higher yield, and cultivating rice under irrigation had positive influence on adoption of improved rice varieties. Adopters increased their net income per ha by GH¢374.6 whereas the potential gain to the non-adopters had they adopted would have been GH¢867.5. Therefore, the adopting households were better off than non-adopters. The average exposure rate and adoption rate of improved rice varieties were 82.5% and 67.2% respectively. These findings will aid effective planning of dissemination activities by agricultural extension agents to increase the diffusion and adoption of improved rice varieties by farmers to increase their net rice income.

Key words: *Adoption; non-exposure bias; selection bias; switching regression; rice*

INTRODUCTION

Ghana depends on imports due to a deficit in domestic rice production (Amanor-Boadu, 2012; Bruce *et al*., 2014). In order to narrow the gap between domestic demand and supply of high-quality rice, Ghana's rice development strategy seeks to achieve a 10% annual rise in output, although the growth rate between 2010-2016 was 39.8% (MoFA, 2018). The deficit[1] in national output has been attributed to low yield (3.28mt/ha) which is less than half of the achievable yield of 6-8mt/ha (Ragasa *et al.,* 2013; MoFA, 2016 and 2021). Therefore, in order to boost yields, improved agronomic practices (such as planting improved varieties at optimal

[1] The deficit in national output of milled rice rose from 354,205 to 580,300mt between 2011-2017 (MoFA, 2018).

density, appropriate fertilizer application, lowland rice field water management) have been recommended to farmers (Buah *et al*., 2011; Ragasa *et al.,* 2013; Abdulai *et al*., 2018). Specifically, various rice varieties have been released for cultivation in Ghana with desirable traits such as high yield, early maturity, disease resistance, aromatic and parboiling qualities. The awareness by rice farmers of these improved rice varieties and subsequent adoption supported by complementary inputs should result in higher net rice income through increased output to support household expenditure (Faltermeier and Abdulai, 2009; Tambo and Wünscher, 2014).

This study assesses the true causal effect of adoption on net rice income, while controlling non-exposure bias and the influence of observable and unobservable bias on household net rice income (Duflo *et al*., 2007; Banerjee and Duflo, 2009).

MATERIALS AND METHODS

Description of the Study Area and Sampling Approach

This study uses 2012/2013 production data of 576 Ghanaian households obtained from the International Food Policy Research Institute (IFPRI) office in Ghana. Proportional probability sampling based on output was applied in initial selection of 25 districts from eight regions[2] whereas random sampling was employed in final selection of districts, communities and households. The eight regions make up about 79.3% of Ghana's total land area (MoFA, 2016).

The data did not have production information on all crops cultivated, animals and other components that constitute household income. Therefore, the direct effect of adoption on net rice income per ha, a sub-component of total household income is estimated.

Treatment effect of adoption of improved rice varieties with correction for exposure

Following Diagne and Demont (2007), exposure is defined as a household being aware of the existence of or has knowledge about improved varieties. This implies exposure is a necessary condition for adoption (Diagne and Demont, 2007). Consequently, non-exposure bias exists because not everyone in the population is exposed due to incomplete diffusion of improved rice varieties (Diagne, 2006) and non-exposed farmers cannot adopt despite the possibility of adopting when exposed.

Thus, where awareness about improved varieties is incomplete, estimating adoption without first estimating the probability of exposure produces the results of joint exposure and adoption, JEA $[P(\omega y = 1) = P(\omega = 1, y = 1)]$ and not adoption alone. The JEA is the average adoption rate under partial exposure because it contains both exposed and non-exposed households from the full sample. Following Diagne (2006), exposure to improved rice varieties is estimated using a probit model for the full sample as:

$$\omega_i^* = k_i'\beta + u_i \quad (1)$$

Empirically, it is estimated as:

$$\omega_i^* = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \beta_5 Z_5 + \beta_6 Z_6 + U_i \quad (2)$$

where ω_i^* is a latent dependent variable of exposure to improved rice (1, exposed, 0, non-exposed); $Z_1 \ldots\ldots Z_6$ are covariates in Table 1 that determine exposure; U_i is an $u_i \sim IIND(0, \sigma^2)$ error term and β_i is vector of parameters to be estimated.

Employing the average treatment effect $[ATE(x)]$ proposed by Wooldridge (2002)

[2] These are Northern, Upper East, Upper West, Ashanti, Greater Accra, Volta, Western, and Eastern Regions.

and Diagne and Demont (2007) based on the conditional independence assumption (Rosenbaum and Rubin, 1983), that exposure status ω is independent of subsequent adoption outcomes once the observed set of covariates that determine exposure are controlled. The $ATE(x)$ measures the average adoption outcome of a rice farming household randomly drawn from the population when every rice farming household is exposed to the improved rice varieties. $ATE(x)$ is estimated only for households with exposure (Diagne, 2006; Diagne and Demont, 2007) as:

$$ATE(x) = E(y_1 - y_0|\omega = 1, x) = g(x, \beta) \quad (4)$$

The switching regression approach

In estimating the impact of adoption on net rice income for households with exposure to improved rice varieties, the propensity score matching (PSM) and switching regression methods are usually applied (Maddala and Nelson, 1975; Angrist, 2001; Amare *et al*., 2012; Noltze *et al*., 2013; Tambo and Wünscher, 2014). Measuring the effect of adoption of improved rice varieties on household net rice income has potential endogeneity because adoption is non-randomly assigned (farmers choose to adopt) leading to self-selection (Ravallion and Wodon, 1998; Baker, 2000; Diagne and Demont, 2007; Phillips *et al*., 2014). More so, adopters may be systematically different from non-adopters and may mask the true effect of adoption of improved rice varieties on household well-being (Burtless, 1995; Duflo *et al*., 2007; Banerjee and Duflo, 2009; Del Carpio and Maredia, 2010; Asfaw *et al*., 2012).

The PSM fails to correct for unobservable bias in adoption behaviour and net rice income of households unlike switching regression (Maddala and Nelson, 1975; Laure, 2007). Switching regression corrects for observable and unobservable bias by estimating separate outcomes (equations 4 and 5) of net rice income per ha for adopters and non-adopters conditional on adoption decision (equation 3) as:

$$P_i = 1(z_i\gamma) + u_i > 0 \quad (3)$$

$$Y_1 = X_1\beta_1 + \mu_1 \quad \text{If } P = 1 \quad (4)$$

$$Y_0 = X_0\beta_0 + \mu_0 \quad \text{If } P = 0 \quad (5)$$

where Y_1 and Y_0 are the net rice incomes per ha for adopters and non-adopters, X_1 and X_0 are the $1 \times n_1$ and $1 \times n_0$ vectors of explanatory variables relevant to each group, β_1 and β_0 are the $n_1 \times 1$ and $n_0 \times 1$ individual specific parameter vectors, γ and $m \times 1$ are parameter vectors of the adoption equation, P is a latent variable determining which group applies, and z_i a $1 \times m$ vector of explanatory variables that explain the probability of adoption and u_i, μ_1, and μ_0 are the error terms.

Following Lee (1978) and Fuglie and Bosch (1995), the error terms u, μ_1 and μ_0 have a trivariate-normal distribution with mean vector 0, and a covariance matrix specified as:

$$cov(u, \mu_1, \mu_0) = \begin{bmatrix} \sigma_u^2 & \sigma_{\mu_1 u} & \sigma_{\mu_0 u} \\ \sigma_{\mu_1 u} & \sigma_{\mu_1}^2 & \sigma_{\mu_1 \mu_0} \\ \sigma_{\mu_0 u} & \sigma_{\mu_1 \mu_0} & \sigma_{\mu_0}^2 \end{bmatrix} \quad (6)$$

where, $(u) = \sigma_u^2$, is 1 because γ can only be estimated up to a scale factor (Maddala 1983). Likewise, $var(\mu_1) = \sigma_{\mu_1}^2$, $var(\mu_0) = \sigma_{\mu_0}^2$, $cov(u, \mu_1) = \sigma_{\mu_1 u}$, $cov(u, \mu_0) = \sigma_{\mu_0 u}$ and $cov(\mu_1, \mu_0) = \sigma_{\mu_1 \mu_0}$.

Selection bias exists when the error terms of adoption and net rice income per ha are correlated. Following Fuglie and Bosch (1995), the expected values of the error terms μ_1 *and* μ_0 are:

$$E(\mu_1|P_i = 1) = \sigma_{\mu_1 u}\lambda_1 \quad (7)$$

$$E(\mu_0|P_i = 0) = \sigma_{\mu_0 u}\lambda_0 \quad (8)$$

The estimates (γz_i) from the selection equation are used to compute the inverse mills ratios, λ_1 and λ_0 which are included in the outcome equations to correct for selection bias (Maddala, 1983) as follows:

$$\lambda_1 = \frac{\phi(z_i\gamma)}{\Phi(z_i\gamma)} \quad \text{for } P_i = 1 \quad (9)$$

and $\lambda_0 = -\frac{\phi(z_i\gamma)}{1-\Phi(z_i\gamma)}$ for $P_i = 0$ (10)

$$Y_1 = X_1\beta_1 + \sigma_{\mu_1 u}\lambda_1 + \xi_1 \ \ if\ P_i = 1 \quad (11)$$

$$Y_0 = X_0\beta_0 + \sigma_{\mu_0 u}\lambda_0 + \xi_0 \ \ if\ P_i = 0 \quad (12)$$

where ϕ and Φ are the probability density functions and cumulative distribution functions respectively of the standard normal variable.

The selection and outcome equations are estimated simultaneously by full information maximum likelihood [FIML] (Lee and Trost, 1978; Greene, 2000; Lokshin and Sajaia, 2004 and 2011; Alene and Manyong, 2007; Di Falco *et al*., 2011). When the estimated covariance $\sigma_{\mu_1 u}$ and $\sigma_{\mu_0 u}$ in the two outcome equations are statistically significant, then adoption decisions and net rice income per ha outcomes are correlated, thus an endogenous switching model and, exogenous switching regression when they are statistically not significant ($\sigma_{\mu_1 u} = \sigma_{\mu_0 u} = 0$).

The FIML can be identified through non-linearities of λ_1 and λ_0 (Lokshin and Sajaia, 2004 and 2011; Di Falco *et al*., 2011). Nonetheless, a better identification requires an exclusion restriction (Asfaw *et al*., 2012; Tambo and Wünscher, 2014) where an instrumental variable that determines a household's decision to adopt improved rice varieties but has no direct impact on household net rice income per ha is used. The validity of the instrument is ascertained using a falsification test (Di Falco *et al*., 2011) and if appropriate, it will only affect adoption decision and not affect the net rice income per ha outcome of non-adopters. The log likelihood function is expressed as:

$$\ln(L) = \sum_{i=1}^{N} P_i \left[ln\Phi\left(\frac{\mu_1}{\sigma_{\mu_1}}\right) - ln\sigma_{\mu_1} + ln\Phi(\varphi_{i1})\right] + 1 - P_i \left[ln\Phi\left(\frac{\mu_0}{\sigma_{\mu_0}}\right) - ln\sigma_{\mu_0} + \ln(1 - \Phi(\varphi_{i0}))\right] \quad (13)$$

where, $\varphi_{ij} = \frac{z_i\gamma + \gamma_i\, \mu_i / \sigma_i}{\sqrt{1} = \gamma_i^2}$ with γ_i denoting the correlation coefficient between the error term u_i of the selection equation and the error terms, μ_1, μ_0 of the outcome equations respectively. The predicted values of net rice income per ha from the FIML are used to estimate the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU). The ATT estimates the difference in net rice income per ha of adopters of improved rice varieties and what their wellbeing would have been if they had not adopted. However, the ATU reveals the difference in net rice income per ha for non-adopters of improved rice varieties and what would have pertained had they adopted (Heckman *et al*., 2001; Di Falco *et al*., 2011). Given a household with characteristics X, the expected value of net rice income per ha for adopting and the counterfactual for non-adoption are:

$$E(Y_1|P_i = 1) = X\beta_1 + \sigma_{\mu_1 u}\lambda_1 \quad (14)$$

$$E(Y_0|P_i = 1) = X\beta_0 + \sigma_{\mu_0 u}\lambda_1 \quad (15)$$

Therefore, the change in net rice income per ha resulting from adoption is:

$$ATT = E(Y_1|P_i = 1) - E(Y_0|P_i = 1) = X(\beta_1 - \beta_0) + \lambda_1(\sigma_{\mu_1 u} - \sigma_{\mu_0 u}) \quad (16)$$

Likewise, for a household with characteristics X, the expected value of net rice income per ha for non-adopting and the counterfactual had it adopted are:

$$E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_1 u}\lambda_0 \quad (17)$$

$$E(Y_0|P_i = 0) = X\beta_1 + \sigma_{\mu_0 u}\lambda_0 \quad (18)$$

The change in net rice income per ha for non-adoption and its counterfactual are:

$$ATU = E(Y_0|P_i = 0) - E(Y_1|P_i = 0) = X(\beta_1 - \beta_0) + \lambda_0(\sigma_{\mu_1 u} - \sigma_{\mu_0 u}) \quad (19)$$

Similarly, the base heterogeneity, BH (Carter and Milon, 2005; Di Falco *et al*., 2011), the difference in net rice income per ha between actual adopters ($E(Y_1|P_i = 1) = X\beta_1 + \sigma_{\mu_1 u}\lambda_1$) and the counterfactual hypothetical adopters ($E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_1 u}\lambda_0$) in the non-adopter households as:

$$E(Y_1|P_i = 1) - E(Y_1|P_i = 0) = X(\beta_1 - \beta_0) + \sigma_{\mu_1 u}(\lambda_1 - \lambda_0) = BH_1 \quad (20)$$

Similarly, the base heterogeneity (BH) for the actual non-adopters ($E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_0 u}\lambda_1$) and their counterfactual hypothetical non-adopters ($E(Y_0|P_i = 0) = X\beta_1 + \sigma_{\mu_0 u}\lambda_0$) in the adopter households as:

$$E(Y_1|P_i = 0) - E(Y_0|P_i = 0) = X(\beta_1 - \beta_0) - \sigma_{\mu_0 u}(\lambda_1 - \lambda_0) = BH_2 \quad (21)$$

Lastly, transitional heterogeneity assesses whether the effect of adoption of improved rice varieties is larger or smaller for the actual adopters or counterfactual adopters in the non-adopter households.

The FIML is estimated for 480 households with exposure to improved rice varieties using the *movestay* command in STATA (Lokshin and Sajaia, 2004). The first stage estimates the determinants of adoption of improved rice varieties followed by the determinants of net rice income per ha for adopters and non-adopters. Household net rice income per ha is calculated as total revenue per ha less total cost of production per ha (including land preparation, seed, fertilizer, herbicides, labour, harvesting, post-harvest operations, marketing and transportation cost).

Table 1 presents a summary definition of variables used in the estimation of the effect of adoption of improved rice varieties on household net rice income per ha in the study area.

Table 1: Summary definition of variables used in net rice income analysis

Variable	Description
Adoption	Dummy; 1 if a household head cultivated at least one improved rice variety, 0, otherwise
Community participation in rice projects	Dummy; 1 if community ever participated in a rice project, 0, otherwise
Model farmer	Dummy; 1 if household head has ever been a model farmer, 0, otherwise
Block farming	Dummy; 1 if household head has ever participated in block farming, 0, otherwise. Block farming was a government intervention that provided farmers with production inputs on credit and extension service to boost arable crops production.
FBO membership	Dummy; 1 if a household member belongs to a farmer-based organization, 0, otherwise
Agricultural extension	Dummy; 1 if household head has access to agricultural extension services, 0, otherwise
Forest zone	Dummy; 1 if agro-ecological area of rice farm is forest, 0, coastal zone

Guinea savannah zone	Dummy; 1 if agro-ecological area of rice farm is guinea savannah, 0, coastal zone
Lowland rain fed	Dummy; 1 if rice cultivation system is lowland rain fed, 0, upland rain fed
Irrigated production	Dummy; 1 if rice cultivation system is irrigation, 0, upland rain fed
Higher yield	Dummy; 1 is whether farmer seeks higher rice yield, 0, otherwise
Market demand	Dummy; 1 is whether farmer produces rice for sale in the market, 0, otherwise. Market demand includes good taste and aroma, ease of milling, long grain, parboiling and swelling properties mostly demanded by consumers.
Own consumption	Dummy; 1 is whether farmer produces rice for household consumption, 0, otherwise
Use of farm saved seed	Number of years farm saved seed of current rice variety was continuously cultivated by household
Farm size (ha)	Number of hectares of cultivated rice per year
Agro-input shop	Dummy; 1 if community has agro-input shop, 0, otherwise
Sex of household head	Dummy; 1 if household head is female, 0, male
Educational level	Number of years of formal education of household head
Last season's crop income	Last season's crop income as proportion of household income (in %)
Rice output	Total tonnes of rice harvested from farm per year
Rice sold (tonnes) per household previous year	Total tonnes of rice from last harvest sold by household
Motorcycle ownership	Dummy; 1 if household owns a motorcycle, 0, otherwise
Bicycle ownership	Dummy; 1 if household owns a bicycle, 0, otherwise
Electricity	Dummy; 1 if household has access to electricity, 0, otherwise
Household size	Number of members in household
Net rice income per ha	Net rice income of a household (in GH¢) divided by the rice farm area in hectares of the household

Source: Author's construction based on survey data set. Currency GH¢ = Ghana cedi.

RESULTS AND DISCUSSION

3.1 Exposure rate and determinants of exposure to improved rice varieties

Following Diagne (2006), exposure is defined as a farmer being aware of the existence of at least one improved rice variety. From Table 2, the predicted average exposure rate to improved rice varieties was about 83%. Community participation in rice project implementation and community agricultural input (agro-input) shops increased exposure to improved rice varieties.

Table 2: Probit results of the determinants of exposure to improved rice varieties

Variable	Coefficient	Standard error	Marginal effect	Standard error
Constant	0.694***	0.098	-	-
Community participation in rice projects	0.407**	0.205	0.086**	0.037
Presence of agro-input shop in community	0.260*	0.148	0.060*	0.032
Model farmer	0.163	0.194	0.037	0.042
Block farming	0.020	0.262	0.005	0.062
FBO membership	0.121	0.132	0.029	0.031
Agricultural extension	0.240	0.162	0.055	0.035
Predicted exposure rate	0.833***	0.015[a]		
Log-likelihood	-250.849			
Chi-squared test statistic	17.35**			
No. of observations	576			

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. [a] standard error calculated using the delta method.

Over 20 rice projects have been implemented in Ghana since 2003 (Ragasa *et al.*, 2013) in collaboration with the agricultural extension service and farmer groups, generating a lot of community awareness about improved varieties. Dalton (2004) found community participation in varietal selection and seed production training increased awareness about Nerica rice in Ivory Coast. Community agricultural input dealers aside selling inputs offer informal advice to farmers including crop varieties to cultivate.

3.2 Determinants of adoption of improved rice varieties

The first stage of the switching regression estimates the determinants of adoption of improved rice varieties only for households exposed to these varieties. The coefficients of many of the explanatory variables statistically influenced adoption decisions. For instance, community participation in rice projects, not only increased awareness about improved rice varieties as in Table 2. It also had positive influence on the decision to adopt improved rice varieties as presented in Table 3. Diagne and Demont (2007) found community participation in varietal selection had positive effect on Nerica rice adoption in Ivory Coast. Similarly, being a model farming household had positive and statistically significant influence on the decision to adopt improved rice varieties. Some of the households in beneficiary rice project communities were selected as model farmers to take part in on-farm varietal trials and demonstrations and promote adoption of improved varieties. This finding is consistent with *a priori* expectation. Household own rice consumption need also had positive influence on improved rice adoption decisions.

Table 3: Results of the adoption selection equation for the switching regression

Variable	Coefficient	Standard error
Constant	0.498	0.461
Community rice project	0.447**	0.222
Model farmer	0.807***	0.232
Block farming	0.106	0.288
Agricultural extension	0.221	0.169
Forest zone	-0.430*	0.237
Guinea savannah zone	-0.891***	0.258
Lowland rain-fed production	0.285	0.271
Irrigated production	1.682***	0.324
Higher rice yield	0.122	0.142
Rice market demand	0.039	0.141
Own consumption of rice	0.260*	0.153
Rice quantity sold (last season)	0.001	0.002
Rice seed recycling	-0.025*	0.015
Farm size	-0.047*	0.025
Agro-input shop	-0.102	0.148
Sex of household head	0.108	0.144
Last season's crop income (as % of household income)	-0.003	0.003
Motorcycle ownership	-0.026	0.159
Electricity access	0.028	0.166
Household size	0.003	0.009
Average adoption rate	0.672***	0.017[a]

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. [a] standard error calculated using the delta method.

Regarding adoption decisions across agro-ecological zones, farm households located in the forest and guinea savannah agro-ecological zones of Ghana, respectively were less likely to adopt improved rice varieties compared with their counterparts located in the coastal zone. These findings are contrary to *a priori* expectation, particularly in the guinea savannah agro-ecological zone, which has been the leading rice-producing zone in Ghana (Ragasa *et al.,* 2013; MoFA, 2016). Nonetheless, as noted by Ragasa *et al* (2014), traditional varieties are still widely planted by farmers in the guinea savannah zone of Ghana. The forest zone is the third largest rice producing zone after the coastal zone (Kranjac-Berisavljevic' *et al.,* 2003; MoFA, 2016).

The cultivation of lowland rice as opposed to upland rice did not statistically affect the adoption of improved rice varieties. This is not consistent with *a priori* expectation given that 78% of national output comes from lowland rain-fed (NRDS, 2009; DFID, 2015). Moreover, majority of improved rice are lowland varieties, except for NERICA and otoomu, which are upland varieties (Ragasa *et al.,* 2013). Additionally, lowland rain-fed cultivation is the most profitable, albeit irrigated production gives the highest yield (NRDS, 2009; CARD, 2010). Likewise, from the results in Table 3, irrigated rice farmers were more likely to adopt improved varieties than upland rice farmers. Irrigated land cultivation represents 16% of national production whereas upland rain-fed is 6%

(NRDS, 2009). Nonetheless, Ghana's irrigation potential remains untapped (Osei-Asare, 2010). The few irrigation schemes are Tono and Vea irrigation schemes in Upper East Region, Kpong, and Afife irrigation schemes in Greater Accra Region, Bontanga and Golinga irrigation schemes in Northern Region that are mostly used for rice and vegetable production during the dry season (CARD, 2010).

On the other hand, use of farm saved seed by a household as well as larger rice farm sizes had negative, but statistically significant effect on improved rice cultivation decision. The repeated cultivation of rice seed taken from the household's own harvested rice was common for both improved and traditional varieties with an average of over four consecutive planting seasons. This is contrary to the recommended practice that encourages farmers to renew their rice seeds at least once every three years (Ragasa *et al.,* 2013). The adopter households in this study generally had smaller farm sizes (3.85 ha) compared with the non-adopters (5.75 ha). This means that adoption was higher amongst smallholder farmers who were also into irrigated rice production. This corroborates the finding by DFID (2015) that rice cultivation is mainly by smallholders. Although Ghana has vast unexploited lowland rain-fed rice fields, access is hampered by land tenure system that limits acreage expansion and investments (NRDS, 2009).

One of the motivations for farmers choosing to cultivate improved rice varieties is to meet household consumption need. Producing for own consumption had positive and statistically significant influence on improved rice adoption decisions. In the study area, rice is grown both for sale and for household consumption albeit quantity sold is higher (1.98tons/ha and 0.90tons/ha for adopters and non-adopters respectively). Rice consumption was slightly higher amongst adopters (0.41 tons/ha) than non-adopter households (0.21 tons/ha).

The effect of adoption of improved rice varieties on household net rice income

In this section, the results of the effect of adoption on household net rice income are discussed. First, the differences in the coefficients of the net rice income per ha between the adopter and non-adopter households indicate the presence of heterogeneity in the sample. Furthermore, the statistical significance (at 1%) of the correlation coefficient (ρ_1) between the error terms of the adoption of improved rice varieties and the net rice income per ha of adopters in Table 4, implies the existence of selection bias. Thus, both observed and unobserved factors influenced the adoption decision of adopters and their net rice income per ha. Therefore, the adoption of improved rice varieties would not have the same effect on the non-adopters should they choose to adopt, as it would on the adopters. On the other hand, the correlation coefficient, ρ_0 between adoption and net rice income per ha was not statistically significant for the non-adopters. This implies the absence of selection bias and the influence of observed and unobserved factors on their non-adoption decisions. The statistical significance (at 1%) of the likelihood ratio tests for independence of equations (H_0: $\rho_1 = \rho_0 = 0$ is rejected) at the bottom of Table 4 indicates joint dependence between the adoption of improved rice varieties and the household net rice income per ha respectively for adopters and non-adopters.

In order to better[3] satisfy the identification condition for the FIML switching regression model (Lokshin and Sajaia, 2004 and 2011; Di Falco *et al*., 2011), an exclusion restriction through an instrumental variable (Asfaw *et al*., 2012; Tambo and Wünscher, 2014) was applied. The exclusion restriction through instrumental variable requires at least one variable that affects adoption decision but has no direct statistically significant effect on the net rice income per ha of non-adopters. The instrumental variable was being a model farmer for the net rice income per ha and its validity was tested using a falsification test (Di Falco *et al*., 2011). The instrument was valid with selection as model farmer having a positive and statistically significant (at 1%) effect on adoption of improved rice varieties, but no statistically significant influence on the net rice income per ha outcome of the non-adopter households.

Next, the results of the determinants of household net rice income per ha conditional improved rice variety adoption presented in Table 4 are discussed. From Table 4, the proportion of last season's crop income relative to total household income had a positive and statistically significant effect on the net rice income per ha of only non-adopters of improved rice varieties. Descriptive statistics of the data revealed that amongst the non-adopters, the mean net rice income per ha were GH¢377.70 and GH¢176.21 respectively for households whose previous crop income contributed more than 50% and less than or equal to 50% of their total income.

The coefficient of guinea savannah, a dummy variable, was negative and statistically significant relative to household net rice income per ha for both adopters and non-adopters of improved rice varieties. This means the net rice income per ha was lower for rice farming households located in the guinea savannah agroecological zone in comparison with those in the coastal zone. The yield, production cost per ha and net rice income per ha in the guinea savannah were 1.81mt/ha, GH¢613.93 and GH¢514.53 for adopters and 1.2mt/ha, GH¢458.10 and GH¢294.75 for non-adopters. Meanwhile, the yield, production cost per ha and net rice income per ha in the coastal zone were 3.62mt/ha, GH¢926.50 and GH¢1336.55 for adopters and 1.87mt/ha, GH¢450.42 and GH¢715.99 for non-adopters.

The size of rice farm in Table 4, indicates that households (both adopters and non-adopters) with smaller farm sizes had a higher net rice income per ha than larger ones. This means households with smaller farm sizes produced a higher yield, which translated into a higher net rice income per ha. The smaller farm sizes were mainly into irrigated rice production, which requires intensive input use, but gives the highest yield in Ghana (NRDS, 2009). Selection as a model farmer had a positive influence on the net rice income per ha only for adopters of improved rice varieties. This implies model farming households who were also adopters of improved rice varieties obtained a higher net rice income per ha. For instance, from the descriptive statistics within the adopting model households the mean farm size, yield, production cost per ha and net rice income per ha were 4.27ha, 2.41mt/ha, GH¢632.44 and GH¢876.39 respectively.

[3] The FIML is identified through the non-linearities of the inverse mills ratios, λ_0 and λ_1(Lokshin and Sajaia 2004), however identification is enhanced by the introduction of an instrumental variable.

Table 4: FIML ESR results on effect of adoption on net rice income

Variable	Net rice income per ha	
	Adopters	Non-adopters
Constant	330.302	-156.452
	(375.627)	(190.534)
Last season's crop income (as % of household income)	0.552	3.154**
	(2.414)	(1.358)
Guinea savannah	-636.42***	-201.881**
	(151.326)	(95.930)
Farm size	-73.071***	- 45.227***
	(15.380)	(5.981)
Model farmer	978.052***	11.967
	(143.621)	(147.744)
Electricity access	151.005	157.141**
	(127.789)	(62.481)
Motorcycle ownership	93.551	143.289**
	(128.049)	(60.650)
Household size	- 12.274	-6.584**
	(8.231)	(3.308)
Lowland rain-fed production	9.484	300.259***
	(298.606)	(99.002)
Irrigated production	1195.789***	471.658**
	(297.027)	(205.318)
Use of farm saved seed	-40.447**	-2.190
	(16.212)	(5.855)
Rice quantity sold	4.549***	7.054***
	(0.465)	(0.620)
$ln\sigma_1, ln\sigma_0$	6.956***	5.784***
	(0.045)	(0.075)
ρ_1, ρ_0	0.923***	-0.294
	(0.026)	(0.276)
LR test of indep. eqns	49.42***	
Log likelihood	-3963.183	
Chi-squared test statistic	430.29***	
No. of observations	480	

****, ** indicate values statistically significant at 1% and 5% respectively. Figures in brackets are the standard errors. $ln\sigma_1$ and $ln\sigma_0$ are the natural logs of the square roots of the variances of the residuals of the net rice income per ha of adopters and non-adopters of improved rice varieties. ρ_1 and ρ_0 are the correlation coefficients of the error terms between the adoption decision and net rice income per ha of adopters and non-adopters respectively. LR test of indep. Eqns (H_0: $\rho_1 = \rho_0 = 0$) value is 49.42 at 1% and H_0 is rejected.*

Regarding household assets, motorcycle ownership had a positive effect on net rice income per ha of non-adopters at 5% level of statistical significance. Amongst the non-adopters, households who owned motorcycles had higher net rice income per ha than those without motorcycles. The mean yield, production cost per ha and net rice income per ha were 1.42mt/ha, GH¢437.35 and GH¢447.82 respectively for non-adopting households that owned motorcycles and 1.25mt/ha, GH¢494.04 and GH¢287.9 for those without motorcycles. Similarly, access to electricity had a positive and statistically significant effect on the net rice income per ha of only non-adopters of improved rice varieties. The mean yield, production cost per ha and net rice income per ha were 1.33mt/ha, GH¢465.50 and GH¢364.23 respectively for non-adopters who had electricity and 1.29mt/ha, GH¢486.96 and GH¢317.21 for those without electricity.

Meanwhile, larger households had a lower net rice income per ha than smaller households amongst the non-adopters. The yield, production cost per ha and net rice income per ha were 1.22mt/ha, GH¢465.55 and GH¢294.08 for non-adopter farmers with a household size of 10 or lower and 1.4mt/ha, GH¢477.97 and GH¢398.59 for household size greater than 10.

Relative to the rice cultivation system, irrigated production had a positive and statistically significant effect on the net rice income per ha for both adopters and non-adopters. The mean farm size, yield, production cost per ha and net rice income per ha for the irrigated rice producers were 2.94ha, 3.9mt/ha, GH¢913.06 and GH¢1521.47 respectively for adopters and 3.92ha, 1.9mt/ha, GH¢508.89 and GH¢726.63 for non-adopters. Although irrigated rice production increased the net rice income per ha, it was higher for adopters than non-adopters of improved rice varieties. Nonetheless, lowland rice production also had a positive and statistically significant influence on the net rice income per ha amongst non-adopters of improved rice varieties. The mean farm size, yield, production cost per ha and net rice income per ha for lowland rainfed rice producers were 4.56ha, 1.91mt/ha, GH¢613.38 and GH¢583.33 for adopters and 6.13ha, 1.3mt/ha, GH¢453.01 and GH¢361.02 for non-adopters.

Meanwhile, use of farmer saved seed had a negative impact on net rice income per ha only for adopters of improved rice varieties. The yield, production cost per ha and net rice income per ha were 3.25mt/ha, GH¢745.25 and GH¢1288.79 for adopting households who used new improved varieties at least once every three years and 2.61mt/ha, GH¢732.60 and GH¢897.40 for using farm saved seed beyond three years. This means that the planting of farm saved seed amongst the adopter households reduced their net rice income per ha. The recommended practice is that farmers renew their rice seeds at least once every three years (Ragasa *et al.,* 2013).

Lastly, the quantity of rice sold the previous year by a household had a positive and statistically significant effect (at 1%) on its net rice income per ha respectively for both adopters and non-adopters of improved rice varieties. The mean quantities of rice sold the previous season were 1.98 and 0.90mt/ha respectively for adopting and non-adopting households.

Conditional Expectations, Treatment, and Heterogeneity Effects

The predicted values of household net rice income per ha are obtained from the FIML ESR results in Table 4. The predicted values are used to estimate both the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). The ATT estimates the difference in household net rice income per ha of adopters (in cell (a) of Table 5) and what their wellbeing would have been if they had not adopted (in cell (c) of Table 5) improved rice varieties. On the other hand, the ATU indicates the difference in net rice income per ha for non-adopters (in cell (b) of Table 5) and the counterfactual (in cell (d) of Table 5) had they adopted (Heckman *et al*., 2001; Di Falco *et al*., 2011).

From Table 5, the observed net rice income per ha of the adopters of improved rice varieties (in cell (a)) was GH¢ 1032.641. On the other hand, the observed net rice income per ha of non-adopters of improved rice varieties (in cell (b)) was GH¢ 349.870. The observed difference in net rice income per ha between the adopters and non-adopters reveal that adopting households on average, obtained an additional net income per of GH¢ 682.771. However, Carter and

Milon (2005) note that this comparison is inappropriate becuase it does not take into account unobserved factors that might have influenced net rice income per ha.

The treatment effect of adoption for the adopters, also known as the ATT (cell (a) minus cell (c) of Table 5) of improved rice varieties on household net rice income per ha was GH¢ 374.633. This means adopting households increased their net rice income per ha by 56.94% more than what they would have gained if they not adopted. Meanwhile, the treatment effect of the non-adopter households had they chosen to adopt (cell (d) minus cell (b) of Table 5) would have been GH¢ 867.458 per ha. This would have translated into a potential increase in net rice income per ha by 247.937% for the non-adopter households, had they decided to adopt improved rice varieties. This implies that both groups (adopters and non-adopters) stand to increase their net rice income per ha as adopters of improved rice varieties.

Table 5: Average expected household net rice income per ha

Net rice income per ha (in GH¢)	Decision stage: To adopt	Decision stage: Not to adopt	Treatment effect	Treatment effect[4] in %
Adopting households	(a) 1032.641 (52.791)	(c) 658.008 (60.479)	374.633*** (25.465)	56.934
Non-adopting households	(d) 1217.328 (29.841)	(b) 349.870 (31.269)	867.458*** (43.440)	247.937
Heterogeneity effects	BH_1 = -184.687 (4.518)	BH_2 = 308.138 (5.120)	TH = -492.825 (0.479)	

****, **, indicate values statistically significant at 1%, and 5% respectively. Figures in brackets are the standard errors. BH and TH are base and transitional heterogeneity respectively. BH_1 is the difference in net rice income per ha in cells (a) and (d). BH_2 is the difference in net rice income per ha in cells (c) and (b). TH is the mean difference in treatment effect between the adopter and non-adopting households.*

The heterogeneity effects accounts for unobserved factors in the net rice income per ha of adopters and non-adopters given their different structural characteristics (Carter and Milon, 2005; Di Falco *et al*., 2011; Asfaw *et al*., 2012). The heterogeneity effects also make it possible to assess the potential effects of adoption of improved rice varieties on net rice income from the counterfactual values in cells (c) and (d) of Table 5. The base heterogeneity of adoption (BH_1) in Table 5, defined as the mean difference in net rice income per ha between actual adopter households (in cell (a) of Table 5) and the counterfactual hypothetical adopters (in cell (d) of Table 5) was negative (-184.687). Therefore, by taking unobserved factors into consideration, the net rice income per ha of the actual adopters in the sample was likely to reduce by GH¢ 184.687.

Similarly, the base heterogeneity of non-adoption (BH_2) in Table 5, defined as the mean difference in household net rice income per ha between the actual non-adopters (in cell (b) of Table 5) and the counterfactual non-adopters (in cell (c) of Table 5) was 308.138. This means that even after accounting for unobserved factors, the adopters had they not cultivated improved rice varieties would have obtained GH¢

[4] This is calculated with respect to the "not to adopt" decision in each case.

308.138 more in net rice income per ha than the actual non-adopters in the sample. This implies the existence of systematic differences between the adopters and non-adopters of improved rice varieties for which the observed determinants of net rice income per ha could not fully account for.

The transitional heterogeneity (TH) effect in Table 5 of household net rice income per ha was negative (-492.825). This implies the effect of treatment (adoption of improved rice varieties) on net rice income per ha in Table 5 was larger for the non-adopting households resulting in a negative value for the transitional heterogeneity. The estimated treatment effects imply that both groups (adopters and non-adopters) as non-adopters would over-estimate the net rice income per ha.

CONCLUSION AND POLICY RECOMMENDATIONS

This study assessed the causal impact of adoption of improved rice varieties on household net rice income per hectare. First, exposure to improved rice varieties was estimated to account for non-exposure bias, followed by the determinants of adoption for the exposed households using the method of treatment effect. Third, the effect of adoption of improved rice varieties on household net rice income per ha was estimated using endogenous switching regression.

From the results, community participation in rice projects and the presence of agricultural input shops in communities enhanced exposure to improved rice varieties. Adoption of improved rice varieties was positively influenced by community participation in rice projects, being a model farmer, participation in block farming, access to agricultural extension services, seeking to obtain higher rice yield, and cultivating rice under irrigation. Larger farm size and use of farm saved seed had negative influence on adoption. The net rice income per ha was higher for households in the coastal zone than the guinea savannah zone although the income effect was greater for the adopters than non-adopters of improved rice varieties. Irrigated rice production offered a higher net rice income per ha albeit higher amongst adopters than non-adopters. Lowland rice production had a positive effect on the net rice income per ha of only non-adopters whereas use of farmer saved seed reduced the net rice income per ha of adopters.

From the empirical results, adopters increased their net rice income per ha by GH¢374.6 (a 56.9% rise). Nonetheless, the potential gain in net rice income per ha to the non-adopters, had they decided to adopt improved rice varieties would have been GH¢867.5 (a 247.9% rise). This means that both groups (adopters and non-adopters) stand to increase their net rice income although, the income effect would have been greater for the non-adopters had they adopted. Therefore, households are better off as adopters than as non-adopters and the adoption of improved rice varieties is an effective strategy to raising household net rice income. The average exposure rate and adoption rate of improved rice varieties were 82.5% and 67.2% respectively. This calls for intensifying of dissemination efforts by agricultural extension officers, to encourage the adoption of improved rice varieties by farmers to increase their net rice income. This is in line with government's goal of poverty alleviation through "investing for food and jobs under the agenda for transforming Ghana's agriculture as outlined by the Ministry of Food and Agriculture in 2018.

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CONFLICT OF INTEREST

None to declare.

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