

DETERMINANTS OF THE ADOPTION OF IMPROVED AGRICULTURAL TECHNOLOGY BY IRRIGATED RICE FARMERS IN NORTH-WESTERN NIGERIA

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Abstract

The study investigated the salient determinants of the adoption of improved agricultural technology of the irrigated rice farmers in north western Nigeria. Cross-sectional data was collected from the 564 irrigated rice farmers selected based on multi-stage sampling technique. The survey data were analysed using the multinomial Instrumented Variable Probit and endogenous switching regression. The results show that age is negatively and significantly related to the adoption of HYVs and combined adoption HYVs and mobile phone. Household size is positively and significantly related to the adoption of HYVs, mobile phone and combined adoption of tractor service and mobile phone. Year of formal education is positively and significantly related to the adoption of HYVs, tractor service and mobile phone. Access to credit is positively and significantly related to the adoption of tractor service only. Farm size is positively and significantly related to the adoption of tractor service and combined adoption of HYVs, tractor service and mobile phone but negatively and significantly related to the adoption of mobile phone, combined adoption of HYVs and mobile phone as well as combined adoption of tractor service and mobile phone. Frequency of extension contact is positively and significantly related to the adoption of mobile phone, combined adoption of HYVs and mobile phone as well as combined adoption of tractor service and mobile phone. Availability of technology is positively and significantly related to the adoption of the combined three technology alternatives. Also, the adoption of mobile phone is likely to increase the technical efficiency of the irrigated rice farmers by 2.426 percentage points and technical efficiency-increasing effect for adopters is 1.340 with 0.364 technical efficiency-decreasing effects for non-adopters. It is concluded that adoption of mobile phone has causal positive effect on the technical efficiency of the adopters and their non-adopters likewise. Therefore, there is the need for encouraging multiple technology adoption and promoting mobile phone adoption among non-adopter irrigated rice farmers.

Keywords: Adoption, Determinants, Irrigated Rice Farmers, Improved Agricultural Technology, North-Western, Nigeria.

Introduction

Improved agricultural technology had been justified as an important vigor for boosting farm output and improving agriculture as whole globally (OECD, 2001; Sarkar & Gosh, 2013). It refers

to the application of improved farm seeds, tractor service and information devices in the farming practice (Otchia, 2014). Varied forms of Improved Agricultural Technology are being used around the globe whose adoption is influenced by internal and external forces. In developing nations of Africa, where agriculture contributes the largest percentage of GDP, the need to critically look at country specification and its appropriate adoption of technologies is called for in order to help in addressing hunger and food insecurity (Zegeye et al., 2022). Nigeria is part of world's nations that struggle hard to minimize the deficit in rice supply and meet up with the requirement of United Nations of Zero Hunger by halving per capita food waste and reduction of food losses in production and supply so as to attain the Sustainable Development Goals II by 2030 (Obayelu, Adeoti & Dontsop). Therefore, the Nigeria's 2020 Voluntary National Review (VNR) on Sustainable Development Goals policies focuses toward addressing food crises, but rice farming in the country remains insufficient and its supply fails to meet expectations (Saka & Lawal, 2019).

Friday (2022) observed that Nigerian rice farmers need to properly adopt improved agricultural technology particularly improved varieties, tractor services and information devices as an option to attain self-sufficiency in rice farming, but amidst the potentiality farming facilities in North-Western Nigeria self-sufficiency in rice production is yet to be attained (Mohammed et al., 2019). Consequently, huge amount of money is spent yearly by various governments in the country in order to close the domestic rice supply deficit. To support this fact, between 1960 and 1990, Nigeria spent a total of ₦5,017.52 billion on rice importation (Anyanwu et al., 1997). The improvement in domestic rice production for the past 8 years, thought resulted to a serious drop in the quantity of imported rice from 1.2 million metric tonnes by the year 2014 to only 438,000 metric tonnes in 2022 but total rice supply still could not keep pace with the rising demand (Ariemo, 2023).

Current research, like that conducted by Houmy et al. (2013); Sarkar and Gosh (2013); Adeola and Oluwafemi (2014); Zhiyong (2015); Falkone and Rosenberg (2022), has demonstrated that enhanced agricultural technology such as the Higher Yielding Variety Seeds, usage of tractor, and information technology is one of the most successful methods for dealing with food self-insufficiency internationally and in Nigeria. However, Nigerian rice farmers are primarily smallholders and usually resisting to changes (GEMS4, 2019). Because of this, they have adopted relatively little new agricultural technology, which has prevented them from producing the necessary rice yields to support the country's achievement of rice farming sufficiency (Umeghalu, Okonkwo & Nwuba, 2012). Only 13% of farmers in North Western Nigeria are using modern agricultural technology, and only 32% of them are using irrigation, according to additional reports from GEMS4 (2019). It follows that the rice farmers are not using their full potential in terms of technical efficiency; their irrational use of technology, including cell phones, tractor services and improved seeds have a negative impact on their lives by lowering rice yields.

Numerous empirical investigations were conducted (see for instance, Obayelu, Adeoti & Dontsop, 2017; Abdulrahman et al., 2018; Adela & Aurbacher, 2019; Geffersa et al., 2019; Baiyegunhi, Akinbosoye & Bello, 2022; Chen et al., 2022; Zegeye et al. 2022) to examine the wide range of problems influencing rice production. AS recommended by the by OECD (2021), these earlier researches did not, however establish a connection between the uptake of mobile phones and the technical efficiency of irrigated rice farmers. This study used Endogenous Switching Regression (ESR) that accounts for selectivity bias to examine the roles that mobile phones adoption plays. This entails examining the factors that influence irrigated rice farmers in North-Western Nigeria to embrace better agricultural technology and examining the connection

between mobile phones' adoption and technical proficiency. The study is divided into five sections; the remaining sections include clarification of the literature, methodology, results and discussion, and conclusion.

Literature Review

This section covers reviews of various literature related to the study comprising conceptual clarification, theoretical framework and empirical studies.

Conceptual Clarification

According to Mamm and Wustemamm (2010), efficiency means the ability to achieve an end result with little or no waste of effort or energy. Technical Efficiency on the other hand is defined by Chen et al. (2022), as the ratio of the actual output to the maximum obtainable output given the available technology at hand. In this study, technical efficiency is operationalized as the difference between expected and actual rice yields, measured in kg. Rice is defined as a short, narrow white or brown grain which is usually grown in the wet land mostly in hot countries as a food (Black, 2023). This definition recognized rice as grain and produces in wet land as justified by Norman and Kebe (2014); Ifeanyichukwu et al. (2016). Drayer (2017), sees rice as a staple food crop for many people over the globe, technically a seed and is carbohydrate-rich grain with varying size and colour popularly used in Asia and Africa. Modernization made irrigation one of the farming options that can help farmers to increase output and gains by engaging in year round farming activities. Proper irrigation is important for reliable crops growth and costs' production. According to Aiyedun (2021), irrigated farming has to do with supply of water by farmers in order to grow crops and postures. To Sarkar and Gosh (2013), irrigated farming has to do with application of water to plants in order meet up their water requirement artificially. Similarly, Tashikalma and Ugbehe (2014) defined irrigated farming as a farming of crops by application of water at intervals. In the context of this study, irrigated rice farmers are the rice planters that utilized irrigation facilities during 2023 irrigated seasons.

Agricultural technology is a term which comprises the application of manual and beast operated apparatus as well as power-driven machineries used to reduce human efforts, improve the timelessness and excellence of most farming with an intention to increase farm yields, quality of farm products and the entire farming efficiency (Anazodo, 1975). In the word of Kusz (2014), agriculture technology is a means of promoting farming system from conventional labour-based to technology-based. Improved agricultural technology is conceptualized as parcel of technology used to promote sensible farming, enlarge output, decrease losses in crop and enhance excellence of farm produce (Tewari et al., 2012). Agricultural technology in this study covers the use of mobile phones by small scale irrigated rice farmers to support their farming practices.

Theoretical Framework

The study's foundation is Expected Utility Theory, also known as Standard Rational Choice Theory, which is attributed to the mathematician, Daniel Bernoulli of the seventeenth century. According to this theory, a person's risk preferences can be expressed as a linear function of the utility of each technology option multiplied by the option's probability under specific assumptions (Ogu, 2013). The rationale behind using this theory as a framework is that farmer's decision on the adoption of agricultural technology is often made in the face of uncertainty or risk, which forces them to prioritize their option based on predicted value.

Empirical Literature

To analyze the relationship between the determinants of agricultural technology and technical efficiency, a study conducted by Blasch et al. (2022) using multinomial logit, mixed logit and latent class logit found out that the knowledge of other farmers who have prior experience with adoption has a positive impact on the valuation of precision farming technology. Ouattara et al. (2022) used multivariate Probit model to investigate the determinants of rice farming systems choice in Cote d'Ivoire, and found out non-uniform determinants of the RFSs choice. Also, among the major factors that determined different RFS choices were land term, irrigation system, intercropping system, access to extension services, membership in cooperative association, access to availability, marketing, farming experience, non-farm income, gender and household size variations. Also, using panel data covering the years 2010-2019, Pan, Tang and He (2022) examined the agricultural production efficiency of Yangtze River Economic Belt using a 3-Stage DEA Malmquist Model. The results indicated that technical efficiency raised TFP and fosters technological growth. In related endeavor, Massresha et al. (2021) used t-test and Logistic regression to examine perception and factors influencing the adoption of agricultural technology in Amhera Regional State, Ethiopia. The study discovered that families with higher socioeconomic level are more likely to utilize improved seeds, fertilizers and irrigation system. Additionally, Musa et al. (2021) looked into what factors affected Borno farmers' use of mechanized equipment. They analyzed the data using Chi-square and to analyze the data and descriptive statistics and discovered that the socioeconomic status of the farmers and the factors influencing their use had a strong impact on the adoption of technology.

In a different study using SFM and Heckman Selection model, Shi, Paudel and Chen (2021) conducted an empirical study on mechanization and efficiency in rice production in China, the study revealed the mean efficiency of 0.74 which subsequently rose to 0.80 after accounting for self-selection bias. Weiwei, Liwenjun and Yinru (2021), conducted a study using SFM on analyze technical efficiency and factors influencing agricultural production in China. The study discovered that during the period 2007-2017, average efficiency increased with further room for improvement and that technology efficiency varied significantly amongst the provinces. Additionally, by utilizing Stochastic Frontier Model, Obianefo et al. (2020) conducted an empirical study on the technical efficiency of rice farmers in Anambra State Value Chain Development Programme. Their findings show that inefficiency variables account for approximately 3.15% of variation in the farmers' technical efficiency.

Additionally, by using Index, Logit Model and the SFM, Saka and Lawal (2019) looked at the factors that influence the uptake and production of improved rice varieties in Southwestern Nigeria, and discovered that famers responded favourably to the program by using the modified kinds more often. Using descriptive statistics, technology utilization index and the Stochastic Frontier Model, Coker, Ibrahim and Ibeziako (2018) conducted research on the impact of agricultural technology usage on the technical efficiency of Cowpea producers. Their findings indicate a negative correlation between efficiency and agricultural technology use at one percent level. By using Cobb-Douglass production function, Amaechina and Eboh (2017), studied the efficiency of resource usage in rice cultivation in the lower Anambra Irrigation Project and discovered certain signs of resources inefficiency. Obayelu, Adeoti and Dontsop (2017) used Stochastic Frontier Model to examine the technical effectiveness and impact differences between NERICA adopters and non-adopters. The study found that adopters had a positive and substantial impact, whereas non-adopters had the opposite outcome. Lastly, using technology adoption index and employed Logit, Tobit and OLS, Tefere et al. (2016) examined the factors

that influence the adoption and usage of agricultural technology in Ethiopia. Their findings indicated that each of the factors was positively and substantially correlated with the adoption. Similar to this, Becerra-Perez, and Lopez-Reyes (2016) used Stochastic Frontier Model to conduct research on the technical efficiency of corn production in Sinaloa, Mexico; the findings indicate that farmers' efficiency was at a level of 0.54%.

From the foregoing, the study of Blasch et al. (2022) is concerned with farmers' preference for adoption of improved agricultural technology, employing neighbor-farmer's adoption as the determinant of choice of agricultural technology. Though, it established positive link between technology adoption and neighbor-farmer's adoption, but use of Mlogit, Mixed Logit and Latent Class Logit in the estimation could not take care with self-selectivity bias. Studies of Ouattara et al. (2022), Massresha et al. (2021), Musa et al. (2021), Saka and Lawal (2019) and Tefere et al. (2016) are dominantly concerned with farmers' perception and determinants of agricultural technology adoption, employing improved seeds, fertilizers and irrigation system as technology packages. Though, they reported similar results but the techniques applied in data analysis (Tobit, Mprobit, Logit, SFM, OLS) are insufficient to estimate treatment effects which are required in studies of this type. Similarly, the studies of Pan, Tang and He (2022), Shi, Paudel and Chen (2021), Weiwei et al. (2021), Obianefo et al. (2020), Coker et al. (2018), Amaechina and Eboh (2017), Obayelu et al. (2017) and Becerra-Perez and Lopez-Reyes (2016) are basically on production efficiency of the agricultural technology employing improved seeds, pesticides, information on internet and extension service as technology packages. With exception of Chen et al. (2022) and Shi et al. (2021) who applied Endogenous Switching Regression and Stochastic Frontier with Heckman Selection Robust, all other studies used techniques that can neither address self-selectivity or endogeneity.

The existing published literature has arguably done a good job of establishing a clear understanding of the relationship between various technology adoption and technical efficiency among various farmers in Nigeria and beyond, primarily using OLS, SFM, Tobit, Probit, Logit. However, the techniques used by the studies that have already been published could not measure the effect of adoption on non-adopters which leads to selection bias. Additionally, the recommendation of OECD (2021) calls for an examination of the role of mobile phones on rice farmers' technical efficiency, so it is imperative to test this relationship, which this study performed using Endogenous Switching Regression (ESR) and applied mobile phones as technology adopted package. Access to technological information is used as an instrumental variable that was adopted from Zegeye et al. (2022); Chen et al. (2022).

Methodology

This section covers the entire methodologies used in conducting this study. Aspects like description of the study area, research design and techniques of data analyses were all presented.

Description of the Study Area

One of the six geopolitical regions that comprise the country is the North Western Nigeria (Accret, 2023). The region occupies Latitude 8°14'60"N to 14°30'0"N and Longitude 3°30'0"E to 10°24'0"E, and is home to the largest zone in the country, making up roughly 59% of the country's total landmass (Almu, Adesina & Kanmodi, 2019). Five dams, Goronyo Dam of Sokoto State, Tiga and Kafin Chiri Dams of Kano State, as well as Jibiya and Zobe Dams of Katsina State, are used for irrigation (Isaac, 2021; Bosola, 2020). Aridisols in dry land site and Vertisols in fadama sites are physical characteristics of the farmed areas in the North Western Nigeria,

which are classified as lowland and upland (USDA, 1975). The region is a Savannah-type vegetation zone located in the West African Sub-Saharan Sudan belt. An extended dry season, from October to April, is typically dominated by dusty harmattan winds from the Northeast. Annual rainfall averages approximately thirty inches, with the most of the precipitation falling down during the wet season, which runs from May to October (USGS, 1973). Moreover, rain-fed farming dominates the production of rice in the North West (GEMS4, 2019).

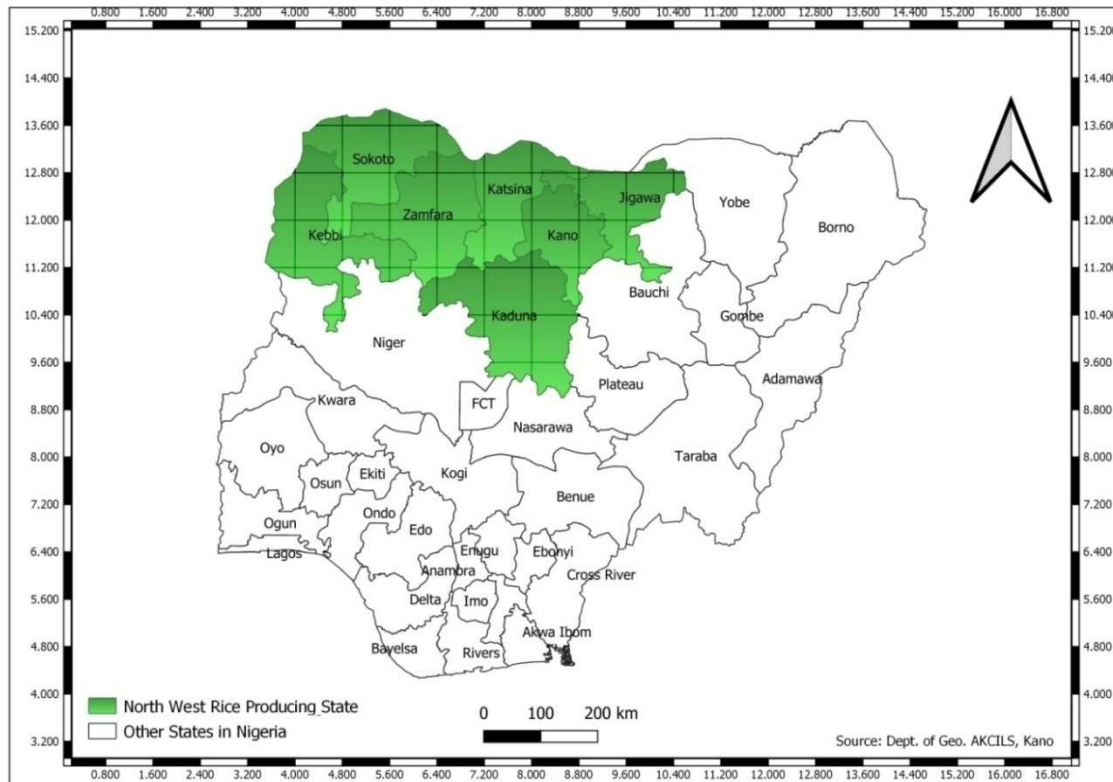


Figure 1: North Western Rice Producing States in Nigeria

Research Design

This study is cross sectional focusing on the experiences of registered irrigated rice farmers in North Western Nigeria with regard to the adoption and use of improved agricultural technology specifically the adoption of mobile phones. The population of the study is all registered irrigated rice farmers in the three states of the North Western Nigeria that it covers, so it covers a total of 542,206 irrigated rice farmers from the states of Kaduna, Jigawa and Kano. The population figure was obtained from the RIFAN office in Kano as well as some readily available documents in Hadeja Jama'are River Basin Development Authority, Kano. The study's sample size was calculated using Yamane formula (1967). Thus;

$$n = \frac{N}{1 + N(e)^2} = \frac{542,206}{1 + 542,206(0.05)^2} = 400 \dots \dots \dots (i)$$

Furthermore, the formula proposed by Fox, Hunn and Mathers (2009) was utilized to account for non-response error/bias. This calculation recommended reducing the previous sample size by the respondents' response rate in order to get more representative sample components. Thus;

$$\therefore n_2 = \frac{400}{0.7} = 571 \text{ irrigated rice farmers.}$$

With respect to the sampling technique, multi-stage sampling was used to select the irrigated rice farmers across the areas of study. In the first stage, the 7 rice producing states were stratified into high, medium and low size of land mass from which Kaduna (among high); Jigawa (among medium) and Kano (among low) were selected. In the second stage, in order to give equal chance to the bigger and smaller rice producing local governments, the local governments were stratified according to high, medium and low number of irrigated rice farmers. Therefore, Makarfi, Ringim and Kura (among the high); Soba, Hadejia and Doguwa (among the medium) and Kudan, Gwiwa and Bunkure (among the low) were chosen from Kaduna, Jigawa and Kano States respectively. In the third stage, enumeration of villages/clusters in each of the local government selected was carried out systematically by taking 1 as a common random start across the local governments and determined 3, 5 and 3 as the skip intervals for Kaduna, Jigawa and Kano respectively. Therefore, Makarfi, Soba and Hunkuyi were selected from Makarfi, Soba and Kudan Local Governments of Kaduna State; Gujaba, S/Garu and Wailare were selected from Ringim, Hadejia and Gwiwa Local Governments of Jigawa State; and Kura and Bagau, Doka Sati and Zangon Buhari were selected from Kura, Doguwa and Bunkure Local Governments of Kano State. Lastly, in the fourth stage sampling of 571 individual irrigated rice farmers from the list of enumerated villages is based on the farmers' availability in each village as did by Obayelu et al. (2017). The distribution of the sample farmers can be seen in Table 3.1 below:

Table 3.1: Distribution of the Research Sample Irrigated Rice Farmers

S/N	Name of Strata	Local Government	Selected Villages (Clusters)		Number of Respondents
			Tech. Adopters	Tech. Non-Adopters	
1	Kaduna	Makarfi L.G.A.	Makarfi (49)	Makarfi (30)	79
		Soba L.G.A.	Soba (35)	Soba (20)	55
		Kudan L.G.A.	Hunkuyi (55)	Hunkuyi (35)	90
		Sub-total			224
2	Jigawa	Ringim L.G.A.	Gujaba (24)	Gujaba (24)	48
		Hadejia L.G.A.	Sabon Garu (29)	Sabon Garu (28)	57
		Gwiwa L.G.A.	Wailare (10)	Wailare (7)	17
		Sub-total			122
3	Kano	Kura L.G.A.	Kura (63)	Kura (42)	105
			Bagau 10)	Bagau (4)	14
		Doguwa L.G.A.	Doka Sati (37)	Doka Sati (18)	55
		Bunkure L.G.A.	Z/Buhari (35)	Z/Buhari (16)	51
		Sub-total			225
4	Grand Total				571

Source: Researcher's Computation, 2024

Note: Figure in parenthesis represents the number of sampled irrigated rice farmers

Techniques of Data Analysis

This section presented all the tools used in data analysis comprising Multinomial Instrumented Variable Probit and Endogenous Switching Regression model.

Multinomial (IV) Probit

Multinomial Instrumented Variable (IV) Probit fits models with multiple dichotomous dependent variable, y^* and endogenous covariates (Gefferesa, Agbola & Mahmood, 2019). It can be used to model multinomial Probit when it is suspected that one or more of the covariates (regressors) are correlated with error term (Smith, 2012). To address the endogeneity in a multinomial

discrete choice in the same way, it is explicitly described how endogeneity occurs through the covariance of a multivariate normal distribution (Watanabe & Maryama, 2022). In this study, it addresses the covariance between adoption of technology package and its availability by adopting access to the technology and distance to market as the instrumental variable as used by Zegeye et al. (2022). Firstly, let $y = (y_1, y_2, \dots, y_n)$ denote multinomial discrete choice results from J alternatives for individuals $i \in \{1, 2, \dots, n\}$, where $y \in \{1, 2, \dots, J\}$. The proposed model assumes that the choice results are determined by the latent utilities $y_i^* = (y_{i1}^*, y_{i2}^*, \dots, y_{ij}^*)$, as below:

$$y_i = j \text{ if } \max(y_i^*) = y_{ij}^* \dots \dots \dots (ii)$$

Where y_{ij}^* is the utility of choosing alternative j for individual irrigated rice farmer i and is further specified as below:

$$y_{ij}^* = X_{ij}'\beta_j + Z_{ij}'\Delta_j + \varepsilon_{ij} \dots \dots \dots (iii)$$

Where X_{ij} and β_j are vectors of exogenous variables and corresponding parameters, including the constant, $Z_{ij} = (Z_{i1}, \dots, Z_{il}, \dots, Z_{iL_j})'$, $\Delta_j = (\delta_1, \dots, \delta_l, \dots, \delta_{L_j})'$, Z_{il} and δ_l are vectors of l^{th} endogenous variables and the corresponding parameters, and ε_{ij} is the error term. Then it can be assumed that the endogenous variables to be specified as below:

$$Z_{il} = \begin{cases} Z_{il}^* < 0 & \text{If } Z_{il} \text{ is continuous} \\ I\{Z_{il}^* > 0\} & \text{If } Z_{il} \text{ is binary} \end{cases} \dots \dots \dots (iv)$$

Where $Z_{il}^* = w_{il}'\alpha_l + \mu_{il}$, w_{il} and μ_{il} are vectors of instrumental variables and the corresponding parameters including the constant, and μ_{il} is the error term with zero mean and variance V_l^2 . Note that the variance, V_l^2 is fixed at 1 when Z_{il} is binary. $I\{\cdot\}$ denotes the indicator function defined as 1 if $\{\cdot\}$ is true, otherwise 0.

This study employed `cmp` Stata command to estimate the determinant of improved agricultural technology alternatives adoption among the irrigated rice farmers. There are seven (7) adoption agricultural technology packages adapted from Zegeye et al. (2022) with necessary modifications, the reference group for this study is non-adoption of any technology ($H_0T_0M_0$), which is represented as $j = 0$. Whereas irrigated rice farmers are considered adopters if they adopted at least one improved agricultural technology ($j = 1, 2, 3, 4, 5, 6$ & 7). Therefore, 1, 2, 3, 4, 5, 6, and 7 stand for adoption of HYVs, adoption of tractor service, adoption of mobile phone, combined adoption of HYVs and tractor service, combined adoption of HYVs and mobile phone, combined adoption of tractor service and mobile phone and combined adoption of HYVs, tractor service and mobile phone, respectively.

The outcome equations for each regime j will be specified thus:

$$\begin{cases} \text{Regime 0: } Non - Adoption_{i0} = X_{i0}\beta_0 + \mu_{i0}Ifj = 0 \\ \vdots \\ \text{Regime } j: Adoption_{ij} = X_{ij}\beta_j + \mu_{ij}Ifj = j, 1, 2, 3, 4, 5, 6, 7 \end{cases} \dots \dots \dots (v)$$

Endogenous Switching Regression (ESR)

Irrigated rice farmers' decision to adopt mobile phone may be self-selected which may result to a potential self-selectivity bias (Zegeye et al., 2022; Chen et al., 2022). In order to address this bias, the Endogenous Switching Regression consisting of treatment equation and two outcome equations are widely used in economic literature (Chen et al., 2022). In this study, expected utility framework will be adopted to analyse the irrigated farmer's decision to use mobile phone

following the work of Chen et al. (2022) with little modifications. Here, D_i^* indicates the difference in the utility between adoption and non-adoption of mobile phone. An irrigated rice farmer would adopt the mobile phone if $D_i^* > 0$, and not adopt mobile phone when $D_i^* \leq 0$. Hence, the irrigated rice farmers' decision to adopt the mobile phone is modeled as:

$$D_i^* = X_i\beta + \varepsilon_i, D_i = \begin{cases} 1 & \text{if } D_i^* > 0 \\ 0 & \text{if } D_i^* \leq 0 \end{cases} \dots \dots \dots (xi)$$

Where D_i is a dummy variable that is equal to one if an irrigated rice farmer adopted mobile phone and zero otherwise; X_i are factors influencing the farmers' decision to adopt mobile phone; β s are coefficients to be estimated; and ε_i is a random error term with a zero mean. In addition, besides adoption of mobile phone, there are other factors affecting technical efficiency of the irrigated rice farmer. Thus, two outcome equations will be specified as below:

$$TE_{1i} = Z_i\delta_i + \mu_{1i} \text{ if } D_i = 1 \dots \dots \dots (xii)$$

$$TE_{0i} = Z_i\delta_0 + \mu_{0i} \text{ if } D_i = 0 \dots \dots \dots (xiii)$$

Where 1 and 0 indicate irrigated rice farmers adopted and not adopted of mobile phone, respectively; TE_{1i} and TE_{0i} indicate technical efficiency in irrigated rice production among farmers adopting and not adopting mobile phone, respectively; Z_i indicates exogenous factors affecting technical efficiency; δ_i and δ_0 are coefficients to be estimated; and μ_{1i} and μ_{0i} are random error terms with zero means.

Given the presence of the self-selectivity bias, the expected average technical efficiency in the actual and counterfactual situations among farmers adopting mobile phone is:

$$E(TE_{1i}/D_i = 1) = Z_i\delta_1 + \sigma_{\theta\mu_1}\gamma_{1i} \dots \dots \dots (xiv)$$

$$E(TE_{0i}/D_i = 1) = Z_i\delta_0 + \sigma_{\theta\mu_0}\gamma_{1i} \dots \dots \dots (xv)$$

Where $\sigma_{\theta\mu_1}$ is the covariance of θ_i and μ_{1i} ; $\sigma_{\theta\mu_0}$ is the covariance of θ_i and μ_{0i} ; and $\gamma_{1i} = \varphi(X_i\beta)/\tau(X_i\beta)$ indicates the inverse Mills ratio. Note that $\varphi(\cdot)$ indicates the standard normal probability density, and $\tau(\cdot)$ indicates the cumulative distribution function of the standard normal distribution. The difference in the expected average technical efficiency in rice production in the actual and counterfactual situations among farmers adopting mobile phone, referred to as the average treatment effect on the treated (ATT), is specified as below:

$$ATT = E(TE_{1i}/D_i = 1) - E(TE_{0i}/D_i = 1) = Z_i(\delta_1 - \delta_0) + \gamma_{1i}(\sigma_{\theta\mu_1} - \sigma_{\theta\mu_0}) \dots \dots (xvi)$$

Let σ_{θ} , σ_{μ_1} and σ_{μ_0} denote the standard deviations of θ_i , μ_{1i} and μ_{0i} , respectively. Thus, $\rho_{\theta\mu_1} = \sigma_{\theta\mu_1}/\sigma_{\theta}\sigma_{\mu_1}$ indicates the correlation coefficient between θ_i and μ_{1i} , and $\rho_{\theta\mu_0} = \sigma_{\theta\mu_0}/\sigma_{\theta}\sigma_{\mu_0}$ indicates the correlation coefficient between θ_i and μ_{0i} . The significant $\rho_{\theta\mu_1}$ and $\rho_{\theta\mu_0}$ indicates the presence of self-selectivity bias.

To estimate the endogenous switching regression model, at least one instrumental variable is required; here accessibility of technology as used in Chen et al. (2022); Wu (2022); Zegeye et al. (2022) is adopted. The instrumental variable should be included in X_i but not included in Z_i . Meanwhile, it should be correlated with the availability of improved agricultural technology, but not correlated with adoption of technology (Chen et al., 2022).

Results and Discussion

This section presented the empirical results of the descriptive and inferential tools used in the study, interpretation of the major research findings and discussions.

Descriptive Statistics

Table 1 reports the descriptive results of socio-economic characteristics of the irrigated rice farmers and the explanatory variables for the eight (8) improved agricultural technology alternatives. The independent variables' mean value for non-adoption of the technology ($H_0T_0M_0$) is used here as a base category for comparison with the mean values of adopter irrigated rice farmers ($H_1T_0M_0$ for adoption of HYVs only, $H_0T_1M_0$ for adoption of tractor service only, $H_0T_0M_1$ for adoption of mobile phone only, $H_1T_1M_0$ for combined adoption of HYVs & tractor service, $H_1T_0M_1$ for combined adoption of HYVs & mobile phone, $H_0T_1M_1$ for combined adoption of tractor service & mobile phone, $H_1T_1M_1$ for combined adoption of HYVs, tractor service & mobile phone).

Table 1. Socio-Economic Characteristics of Sampled Irrigated Rice Farmers

Variables/ $H_0T_0M_0(0)$	$H_1T_0M_0(1)$	$H_0T_1M_0(2)$	$H_0T_0M_1(3)$	$H_1T_1M_0(4)$	$H_1T_0M_1(5)$	$H_0T_1M_1(6)$	$H_1T_1M_1(7)$
Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
AGE (40.304)	38.048	30.600	41.382	43.229	30.000 ²	27.000	35.833 ³
HSZ (9.870)	4.619 ²	1.600	3.426 ¹	13.571	5.000	11.591 ³	11.722 ²
YED (1.255)	3.381 ²	2.700 ¹	3.154 ²	3.400	1.259	1.636 ³	2.831 ¹
AOL (0.503)	0.119	0.050 ¹	0.301 ²	0.629 ²	0.103	0.409	0.466 ²
FSZ (7.593)	6.167 ²	1.000 ²	2.853 ²	10.743	1.914 ²	8.955 ²	10.389 ²
FXC (3.915)	6.081	6.000	4.100 ¹	4.267	1.731 ²	0.864 ²	4.561 ²
GEN (0.863)	0.762 ²	0.900 ¹	0.875 ²	0.914 ¹	0.741 ²	0.727 ²	0.956 ¹
DIS (5.590)	5.667 ²	3.000 ²	6.265 ²	9.000 ²	2.828 ²	4.000 ¹	7.211 ¹

Source: Researcher's Estimation Using Stata 14.

SE=Standard Error in Parenthesis; the Signs (^{1,2,3}) represent level of significance @ 10%, 5% and 1% respectively.

Note: The Mean Comparison of t-test is used to compare the mean of explanatory variables between non-adopters ($H_0T_0M_0$) and adopters of each technology package and their combinations. The signs ^{1,2} and ³ represents level of significance @ 10%, 5% and 1% respectively.

Table 1 results indicated that t-test average comparisons show some heterogeneity level between farmers that adopted and those that did not adopt, and across the adopters of the mobile phones. The average age of non-adopters of improved technology is about 40.304, that of adopters of package 5(combined adoption of HYVs & mobile phone) and 7(combined adoption of HYVs, tractor service and mobile phone) are 30.000 and 35.833 found statistically and significantly different at 5% and 1% levels. While the average age difference between adopters of other technology packages and non-adopters are statistically the same. The average household size of non-adopters of improved technology is about 9.870, that of adopters of package 1(adoption of HYVs), 3(adoption of mobile phone), 6(combined adoption of tractor service and mobile phone) and 7(combined adoption of HYVs, tractor service & mobile phone) are 4.619, 3.426, 11.591 and 11.722 found statistically and significantly different. While the mean household size difference between adopters of other technology packages and non-adopters are statistically the same.

The average year of formal education for non-adopters of improved technology is about 1.255, that of adopters of package 1(adoption of HYVs) and 3(adoption of mobile phone) are 3.381 and 3.154 respectively, found statistically and significantly different at 5% levels; that of package 6(combined adoption of tractor service & mobile phone) is 1.636 statistically and significantly different at 1% level and that of 2(adoption of tractor service) and 7(combined adoption of HYVs, tractor service & mobile phone) are 2.700 and 2.831 respectively, found statistically and significantly different at 10% levels. While the average year of formal education difference between adopters of other technology packages and non-adopters are statistically the same. The average access to credit of non-adopters of improved technology is about 0.503, that of adopters of package 2(adoption of tractor service), 3(adoption of mobile phone), 4(combined adoption of HYVs & tractor service) and 7(combined adoption of HYVs, tractor service & mobile phone) are 0.050, 0.301, 0.629 and 0.466, respectively found statistically and significantly different all at 5% level with exception of 2 which is at 10%. While the mean access to credit difference between adopters of other technology packages and non-adopters are statistically the same.

Also, the average farm size of non-adopters of improved technology is about 7.593, that of adopters of package 1(adoption of HYVs), 2(adoption of tractor service), 3(adoption of mobile phone), 5(combined adoption of HYVs and mobile phone), 6(combined adoption of tractor service & mobile phone) and 7(combined adoption of HYVs, tractor service & mobile phone) are 6.167, 1.000, 2.853, 1.914, 8.955 and 10.389, respectively found statistically and significantly different each at 5% level. While the mean farm size difference between adopters of technology package 4(combined adoption of HYVs & tractor service) and non-adopters are statistically the same. The mean frequency of extension contacts for non-adopters of improved technology is about 3.915, that of adopters of package 3(adoption of mobile phone) is 4.100 found statistically and significantly different at 10% level, that of packages 5(combined adoption of HYVs & mobile phone), 6(combined adoption of tractor service & mobile phone) and 7(combined adoption of HYVs, tractor service & mobile phone) are 1.731, 0.864 and 4.561, respectively found statistically and significantly different each at 5% level. While the average frequency of extension contacts difference between adopters of other technology packages and non-adopters are statistically the same. The mean gender of non-adopters of improved technology is about 0.863, that of adopters of package 1(adoption of HYVs), 3(adoption of mobile phone), 5(combined adoption of HYVs & mobile phone) and 6(combined adopters of tractor service & mobile phone), are 0.762, 0.875, 0.741 and 0.727 respectively, found statistically and significantly different each at 5% level; that of packages 2(adoption of tractor service), 4(combined adopters of HYVs & tractor service) and 7(combined adoption of HYVs, tractor service & mobile phone) are 0.900, 0.914 and 0.956 respectively, found statistically and significantly different each at 1% level.

The average distance to market for non-adopters of improved technology is about 5.590, that of adopters of package 1(adoption of HYVs), 2(adoption of tractor service), 3(adoption of mobile phone), 4(combined adoption of HYVs & tractor service) and 5(combined adoption of HYVs & mobile phone) are 5.667, 3.000, 6.265, 9.000 and 2.828 respectively, found statistically and significantly different each at 5% level; that of 6(combined adoption of tractor service & mobile phone) and 7(combined adoption of HYVs, tractor service & mobile phone) are 4.000 and 7.211 respectively, found statistically and significantly different each at 1% level.

Determinants of the Adoption of Improved Agricultural Technology Alternatives

Table 2. Factors that Determine the Adoption of Improved Agricultural Technology

Alternative Improved Agricultural Technology Adoption Packages							
Var	H ₁ T ₀ M ₀ (1)	H ₀ T ₁ M ₀ (2)	H ₀ T ₀ M ₁ (3)	H ₁ T ₁ M ₀ (4)	H ₁ T ₀ M ₁ (5)	H ₀ T ₁ M ₁ (6)	H ₁ T ₁ M ₁ (7)
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
AGE	-.261(0.28) ³	-0.208(0.40)	-0.751(0.18)	0.338(0.42)	-0.119(0.89) ²	-0.169(0.08)	-0.273(0.2)
HSZ	0.818(0.15) ²	-0.332(0.91)	0.716(0.12) ²	-0.396(0.18)	0.887(0.28)	-0.526(0.15) ²	0.164(0.06)
YED	0.742(0.38) ²	0.236(0.91) ¹	0.809(0.26) ²	0.197(0.27)	0.229(0.42)	0.179(0.58)	-0.308(0.25)
AOL	0.513(0.64)	0.244(0.91) ¹	2.659(0.63)	0.700(0.82)	-0.231(0.64)	-0.146(1.09)	-0.439(0.44)
FSZ	-0.158(0.20)	0.291(0.28) ²	-.317(0.10) ²	0.157(0.16)	-0.896(0.31) ²	-0.200(0.12) ²	0.120(0.04) ³
FXC	0.118(0.18)	0.200(0.95)	0.468(0.11) ²	-0.163(0.29)	0.996(0.35) ²	0.645(0.28) ²	0.018(0.08)
TEA	0.564(0.42) ²	0.505(0.30) ¹	0.608(0.35) ³	0.401(0.46) ¹	0.188(0.28) ²	0.267(0.33) ²	0.323(0.08) ³
Inst1	0.432(0.42) ³	0.129(0.04) ²	0.101(0.11) ³	0.389(0.92)	0.549(0.23)	0.028(0.01) ¹	0.019(0.07) ¹
Inst2	0.214(0.19)	0.116(0.12) ²	0.049(0.13)	0.419(0.62) ³	0.125(0.02) ¹	0.191(0.18)	0.773(0.07) ²
Cont	1.913(1.429) ³	1.201(16.602)	3.142(0.99) ³	4.982(4.856) ²	2.646(7.0)	8.559(2.81) ³	1.176(0.91) ³

Source: Researcher's Estimation Using Stata 14.

Model VCE=Robust; Wald Chi2(7)=354; P-Value(0.0000); Number of Observation=413; SE=Standard Error in Parenthesis; the Signs (^{1,2,3}) represent level of significance @ 10%, 5% and 1% respectively.

Table 2, indicated the outcome of Multinomial Instrumented Variable (IV) Probit model with non-adoption of technology (H₀T₀M₀) as the reference category for making comparison with the adoption all other technology, adopted from Zegeye et al. (2022). It reveals that age of the irrigated rice farmer negatively determined the likelihood of adopting packages 1, 2, 3, 4, 5 and 7, only significant at 1% and 5% levels for alternative 1 and 5, indicating that younger irrigated rice farmers are more likelihood to adopt HYVs and combined adoption of HYVs and mobile phone than aged irrigated rice farmers because younger irrigated rice farmers may possess higher formal educational level and may be less risk-averse than their aged counterpart. This result supports the findings of Zegeye et al. (2022), Habtewlod (2021) and Anyenew et al. (2020). Household size of the irrigated rice farmer positively determined the likelihood of adopting technology packages 1 and 3 all statistically significant at 5% level and negatively determine the likelihood of adopting technology package 6 statistically significant at 5% level, indicating that irrigated rice farmer with larger household size is more likely to adopt HYVs and mobile phone, and less likely to adopt combined adoption of tractor service and mobile phone. This is because adoption of technology package 6 may not require more labour force for the farming activities. This result deviates the findings of Zegeye et al. (2022) and Tefera et al. (2020). Also, irrigated rice farmer's year of formal education positively determined the likelihood of adopting technology package 1, 2 and 3, with technology packages 1 and 3 significant at 5% level and technology package 2 significant at 10%, implying that an additional year of formal education is more likely to make irrigated rice farmer adopt HYVs, tractor service and mobile phone than irrigated rice farmer no year of formal education. This is because more formally educated irrigated rice farmer may have more access and ability to serf and assess

relevant information about different technology packages and subsequently take their advantage. This result supports the findings of Zegeye et al. (2022) and Adebayo et al. (2018).

Access to credit is positive but significant determinant of irrigated rice farmer's likelihood of adopting improved agricultural technology package 2, showing that irrigated rice farmer with access to loan is more likely to adopt tractor service those without access to credit. This is because access to credit addresses income limitation suffered by the small scale irrigated rice farmers in purchasing improved agricultural technology packages, thereby opening the door for timely adoption of the technology. This finding is similar to that of Belay and Mengiste (2021); Ayenew et al. (2020); and Belete and Melak (2018). Farm Size of an irrigated rice farmer positively determined the likelihood of adopting technology packages 2 and 7 but negatively determined the likelihood of adopting technology packages 3, 5, and 6 with technology packages 2, 3, 5 and 6 found significant at 5% levels while technology package 7 is significant at 1% level, implying that irrigated rice farmers with larger size of farm land are likely to adopt tractor service and combined adoption of HYVs, tractor service and mobile phone than their counterparts. This is because as the size of farming land increases farmers are more likely to see farming become permanent as a means of life. This result is similar to the findings of Zegeye et al. (2022), Feyisa (2020) and Alwang et al. (2019). Frequency of extension visitations of an irrigated rice farmer positively determined the likelihood of adopting technology packages 3, 5 and 6 all found significant at 5% level, showing that additional day of extension contact is likely to determine the irrigated rice farmer's adoption of mobile phone, combined adoption of HYVs and mobile phone, and combined adoption of tractor service and mobile phone. This is because extension visits keep farmers informed of the availability, accessibility, description and characteristics of improved agricultural technology packages through advisory services and inputs distributions. This result is similar to that of Tefere et al. (2016).

Availability of improved agricultural technology positively determined the likelihood of adopting all the 7 technology packages with technology packages 1, 5 and 6 found significant at 5% levels, packages 2 and 4 found significant at 10% level while packages 3 and 7 found significant at 1% levels. This implies that irrigated rice farmers with availability of improved agricultural technology are more likely to adopt all the available packages than their counterparts. This is because availability of technology of interest to the farmers at ease facilitates its adopt. This finding supports the result of Alwang et al. (2019). Instrumental variable used in this study (access to technological information) is found statistically and positively determinants of the likelihood of adopting the technology packages.

Adoption of Mobile Phone and Technical Efficiency by Irrigated Rice Farmers

The result of the relationship between the adoption of mobile phone and technical efficiency of irrigated rice farmers is estimated using Endogenous Switching Regression and presented in table 4. The χ^2 statistic for the Wald test of independent equations was found significant at 1%, indicating the presence of dependence between the treatment and the two outcome equations. From the result, the correlation coefficient of both $\rho\theta\mu_1(\rho_1)$ and $\rho\theta\mu_0(\rho_0)$ were found significant, confirming the existence of self-selectivity bias from both observed and unobserved factors. This of course indicates the appropriateness of Endogenous Switching Regression. Also, the study tested the validity of the instrumental variable (distance from market) using falsification test (Falco, Veronesi & Yesuf, 2011). The result shows that the instrumental variable used possesses significant relationship with the use of mobile phone.

Table 3. Estimated Results of ESR Model

Variable	Technical Efficiency			ATT	ATU
	Adoption of Mobile Phone	Farmers Adopting Mobile Phone	Farmers Not Adopting Mobile Phone		
TMO		2.426(1.172) ³	0.217(0.071)	1.340 ³	0.364 ³
AGE	-0.359(0.193) ²	0.235(0.287)	0.431(0.437) ³		
HSZ	-0.726(0.569)	0.256(1.351) ³	0.174(0.143)		
YEDU	0.423(0.300) ³	0.827(5.772)	0.590(2.865) ³		
AOL	0.374(0.619)	0.496(0.799)	0.297(0.250) ³		
FSZ	0.084(0.430)	-0.303(1.007)	0.426(0.321)		
TEA	0.832(0.128) ³	0.539(0.216) ¹	0.460(0.341)		
Instr. Var.	0.142(0.541) ³				
Con.					
$\rho\theta\mu_1$		0.384(0.232) ³			
$\rho\theta\mu_0$			0.122(0.372) ³		
Indep. Eqs. (χ^2)	227.59 ³				
N	564	306	258		

Source: Researcher's Estimation Using Stata 17.

Note: Robust standard error are in parenthesis; ¹, ², and ³ represent level of significance at 10%, 5% and 1%.

Table 3, indicated the output of the adoption of mobile phone on technical efficiency of the irrigated rice farmers in the study area. The output of ESR result shows that adoption of mobile phones is likely to raise the technical efficiency of the adopters by 2.426 percentage points higher than non-adopters of the mobile phones. It also reveals that additional year on irrigated rice farmer's age is likely to raise the technical efficiency of non-adopters of mobile phones by 0.431 percentage points higher than the adopters of the mobile phones. One person addition in the irrigated rice farmer's household size is likely to raise the technical efficiency of mobile phone adopters by 0.256 percentage points higher than non-adopters of the mobile phones. Additional year of formal education fails to raise the technical efficiency of mobile phones adopters; this is because an additional year of formal education is likely to raise the technical efficiency of non-adopters of mobile phones with 0.590 percentage points higher than mobile phones adopters.

Also, access to credit fails to raise the technical efficiency of mobile phones adopter irrigated rice farmers; this is because an additional access to credit is likely to raise the technical efficiency of non-adopters of mobile phones by 0.297 percentage points lower that of mobile phones adopters. Availability of improved agricultural technology alternatives is likely to raise the technical efficiency of irrigated rice farmers; this because with an extra technology availability, technical efficiency of mobile phones adopters is likely to raise by 0.539 percentage points higher than non-mobile phones adopters. Instrumental variable (access to technological information) is found positive and significant related to the technical efficiency among mobile phones adopters.

The outcome of the average treatment effects on the treated (ATT) and average treatment effects on the untreated (ATU) show the impact of adoption of mobile phones and the effect due to their inherent characteristics on technical efficiency of irrigated rice farmers. The ESR

estimates of ATT and ATU account for the selection bias that arises from the fact that adoption and non-adoption of the mobile phones may be systematically different. The results indicate that adoption of mobile phones significantly increases the technical efficiency of the adopters with potential of increasing that of the non-adopters if they adopt. Specifically, the causal effect (technical efficiency-increasing effect) of adopting mobile phones for the adopters is about 1.340 representing 27.45% increase in the technical efficiency of the adopters with adoption of the mobile phones. Also, the causal effect (technical efficiency-increasing effect) of adopting the mobile phones for non-adopters is about 0.364 representing 15.76% decrease in their technical efficiency due to their non-adoption of the mobile phones. Therefore, adoption of mobile phones has a positive and significant effect on technical efficiency of irrigated rice farmers and irrigated rice farmers that did not adopt the mobile phones will experience a less significant increase in their technical efficiency if they adopt the mobile phone. This result supports the finding of Chen et al. (2022).

Conclusion and Policy Recommendations

This study identifies the major factors which determine the irrigated rice farmers' adoption improved agricultural technology alternatives and determines the relationship between adoption of mobile phone and technical efficiency of the irrigated rice farmers. From objective one, the seven improved agricultural technology alternatives used are Higher Yielding Variety seeds (HYVs), tractor service, mobile phone and their combinations. The data used in this study were collected using structured questionnaire administered among 571 irrigated rice farmers across Kaduna, Jigawa and Kano States, out of which 564 were successfully retrieved with 98% return rate which is enough to carry out the main estimation and analysis. Multinomial (IV) Probit was estimated using Mixed-Process Regression base on `cmp` Stata command. The result reveals that irrigated rice farmers' adoption decisions of improved agricultural technology are determined by farmers' own socio-economic characteristics, institutional factors and availability of improved agricultural technology. Specifically, an irrigated rice farmer's decision, all things being equal, is positively determined by age, household size, access to credit, farm size, frequency of extension and availability of the technology. The instrumental variables used in this study (access technological information), adopted from Zegeye et al. (2022), is also found significant regressors. From the second objective, the result of Endogenous Switching Regression shows that besides other determinants adoption of mobile phone is likely to increase technical efficiency of irrigated rice farmers by 2.426 higher than non-adopters. Also, after taken care with self-selectivity bias, it was found that the causal effect of adopting mobile phone has 1.340 technical efficiency-increasing effects on adopters with 0.364 technical efficiency-decreasing effects on non-adopters for not adopting the mobile phone. The use of ESR is appropriate when compared with alternative specifications.

The study is vital as it extended the horizon of technology adoption by incorporating mobile phone adoption as an agricultural technology alternative which other studies did not measure in relation to technical efficiency of irrigated rice farmers. Given the statistical significance of the adoption of several technologies and their combinations based on the estimates of Multinomial (IV) Probit, there is the need for making policy aimed at encouraging the mixed technology adoption among the irrigated rice farmers by making them readily available and accessible. Given the positive and significant relationship between adoption of mobile phone and technical efficiency of the irrigated rice farmers and technical efficiency-decreasing effects on mobile phone non-adopters there is the need for promoting the adoption of mobile phone among non-adopters by cutting down the cost of mobile phones.

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