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Agricultural Technology Utilization and the Welfare Outcomes of Smallholder Farming Households in Nigeria: An Insight from Rice Farmers in the Anchor Borrower Programme

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Abstract

The welfare of smallholder farmers in developing economies is often compromised by a dearth of basic livelihood amenities. This resource constraint problem even among beneficiaries of inputs subsidy interventions may override their incentives to adequately utilize improved agricultural technologies for better livelihood outcomes. We therefore explored the technology utilization pattern and the corresponding welfare outcomes of a cross-section of rice farming households in Nigeria under the auspices of the Anchor Borrower Programme. Data analysis was accomplished via mixed methods. Inferential statistics was employed to provide an extensive overview of their technology utilization patterns and welfare outcomes. The instrumental-variable probit regression model was used to consistently analyze the factors that influence rice farmers' probability of participating in the ABP. Lastly, thematic analysis was used to analyze ancillary qualitative information. Our findings show that rice farmers utilize various mix agricultural technologies and the highest proportion was observed for those who opted for inorganic fertilizers and crop protection chemicals marginally and jointly. Their welfare outcomes appear to vary contingent on the choices of technologies utilized. While social group membership is the strongest factor that influences rice farmers' decision to participate in the ABP, diversification of cropping activities proved to be the strongest impediment.

JEL Codes: Q12; QI6; Q18.

1.0 Introduction

Rice is a primary staple for more than half the world's population with Asia, Sub-Saharan Africa (SSA), and South America being the largest consuming regions. Historically, rice production recorded a significant boost since the inception of the green revolution in Asia, resulting mainly from breakthroughs in scientific efforts, that culminated in more widespread use of agricultural technologies (KPMG, 2019). Although Africa is naturally endowed to produce ample rice for its growing populace and, in the long run, generate export revenue (AfricaRice, 2011) regrettably, this is not the case. SSA is a net importer of rice since it consumes more than it produces (USDA-FAS, 2021). This shortfall has been attributed to the over-reliance on the efforts of small-scale resource-poor farmers that cultivate rice under rain-fed conditions (AfricaRice, 2011) and utilize agricultural technologies sub-optimally (Kassie *et al.,* 2015). Nigeria is the leading consumer and importer of rice in Africa with an annual production of 5,500 million tonnes of milled rice as against consumption of about 8,000 million tonnes (USDA-FAS, 2022). Notwithstanding the plethora of evidence on the productivity gains from the cultivation of modern rice varieties, poverty is very pervasive among farming households in Nigeria (Awotide *et al*., 2016). Regrettably, this condition persists because, besides inappropriate cultivation practices, the importance of harnessing the complementarities among agricultural technologies have not been strongly advocated (Kijima *et al.,* 2012) in the national policy space.

The Nigerian government has actively interfered with the rice economy over the last four decades in diverse ways and its overarching goal has remained the attainment of self-sufficiency through efforts geared toward the intensification of local production. In recent times, input subsidy programmes have been the most favoured institutional approach to pursuing rice self-sufficiency and also to support the plight of smallholder farmers in Nigeria. The ongoing Anchor Borrower Programme (ABP) introduced in 2015 is one of the several interventions. Resource constraint issues may override smallholder farmers' incentives to utilize improved agricultural technologies even when the welfare benefits emanating from increased production can render the marginal expenditure worthwhile (Jayne *et al.,* 2018). Without gainsaying the economic potential of subsidizing agricultural inputs for smallholder farmers, substantial uptake of improved technologies has been demonstrated to be the strongest instrument in empowering farmers to be more productive. While subsidies on agricultural inputs promoted by most interventions produce a weak effect on the supply of agricultural output, substantial uptake of agricultural technologies on the other hand has been recounted to have a stronger and enduring impact (Kumar and Joshi, 2014).

According to Brand and Thomas (2013) and Manda *et al.* (2017), farming households differ significantly in the way they respond to development interventions. Although they are expected to adopt a mix of technologies (Kassie *et al.,* 2013; Teklewold *et al.,* 2013; Tsinigo and Behrman, 2017) to deal with myriads of agricultural production constraints, Mutenje *et al.* (2016) asserted that considerable heterogeneity exists in the choice of technologies they opt for across space and socio-economic conditions. Previous scholarships such as Ayinde *et al.* (2018); Kara *et al.* (2019) and Olarenwaju *et al.* (2021) that have examined the welfare outcomes of ABP rice farmers did not account for possible heterogeneity in the utilization of agricultural technologies that might lead to potentially different welfare outcomes among beneficiary farmers. We therefore explored this seemingly discounted yet vital omission because technology utilization among farmers, even for recipients of subsidized inputs is not exclusively binary as previous studies tend to allude implicitly. Also, the welfare outcomes of ABP farmers contingent on their technology uptake choices across the rice production ecologies under which they operated were further compared since rice yield have been reported to differ markrdly across different rice production ecologies. To achieve these, we first highlighted the various self-reported mix of agricultural technologies utilized by rice farmers in the study area. Secondly, the welfare of the respondents proxied by their productivity and poverty outcomes were extensively analysed contingent on their technology uptake choices. Thirdly, the factors influencing the probability of participating in the ABP were examined while controlling for a suspected endogenous covariate. Thus, the following null hypotheses emanating from the research objectives were tested.

H_{01}: participation in the ABP did not significantly incentivize the technology uptake choices of beneficiary rice farmers

H_{02}: the welfare outcomes of ABP farming households do not differ contingent on their technology uptake choices

2.0 Sampling techniques and data types

Data for this study was obtained via a multi-stage sampling procedure. The first stage entailed the random selection of the South-West zone out of the six geopolitical zones in Nigeria. The second stage comprised the purposive selection of Ekiti and Ogun States which are the major rice producing States in South-Western Nigeria. The third stage involved a purposive selection of three Local Government Areas (LGAs) with relatively larger volumes of paddy rice production activities in each of the selected States, culminating in a total of six LGAs for the study. The fourth stage involved a simple random selection of 60 ABP farmers and 40 non-ABP farmers who were located in rice production clusters in each of the selected LGAs. This resulted in a total of 300 farmers from each State and a grand total of 600 farmers for the study. A structured questionnaire was used to elicit relevant information on the respondents' socioeconomic, paddy rice production technologies and welfare characteristics. The qualitative data obtained via focus group discussions with ABP farmers was used to augment the quantitative data obtained via structured questionnaire. Thus, data analysis was accomplished via mixed methods.

3.0 Analytical techniques

3.1 *Joint and marginal probabilities of agricultural technologies utilization among rice farmers*

Following Teklewold *et al.* (2012) and Tsinigo and Behrman, (2017), the proportions of rice farmers that utilized the observed combinations/mix of agricultural technologies were computed using the joint and marginal probabilities distribution. The various agricultural technologies k utilized by the sampled rice farmers in the study area, all the possible mix of agricultural technologies were derived from the list of agricultural technologies that the farmers reportedly utilized, and also, the self-reported combinations of agricultural technologies utilized by the respondents during the field survey exercise are shown in Table 1. Apart from improved rice seeds which stands alone in its category, the other three categories comprised two to three technologies that are quite similar in functionality. This grouping was necessary for computational convenience. Farmers who utilized at least one or more technologies in such categories were regarded as users of the specific category. For instance, farmers who utilized NPK fertilizers only or urea only or both NPK and urea were classified as users of inorganic fertilizers.

With the above consideration, the joint probability of technologies utilization which shows the observed patterns of utilization (d) for the different categories of agricultural technologies k for the respondents n in this study was computed as:

$$pr(d_j) = {}^{fd_j}\Big/_{\sum d_n} \tag{1}$$

Where d_j is the proportion of rice farmers that utilize any of the observed mix shown in Table 3, and d_n is the total number of rice farmers using the various mix of observed technologies.

Table 1: Agricultural Technologies Utilized by Respondents in Paddy Rice Production

k	**Agricultural Technologies**	**Mutually Exclusive Combinations Possible**	**Self-reported mix obtained from field survey $(\boldsymbol{d})$**
A	Agronomic Practices (Transplanting from nursery, row planting, harrowing)	$A_1 I_0 F_0 C_0$, $A_1 I_1 F_0 C_0$, $A_1 I_0 F_1 C_0$, $A_1 I_0 F_0 C_1$, $A_1 I_1 F_1 C_0$, $A_1 I_1 F_0 C_1$, $A_1 I_0 F_1 C_1$, $A_1 I_1 F_1 C_1$	$A_1 I_0 F_0 C_0$, $A_1 I_1 F_0 C_0$, $A_1 I_0 F_1 C_0$, $A_1 I_1 F_1 C_0$ $A_1 I_1 F_0 C_1$, $A_1 I_0 F_1 C_1$ $A_1 I_1 F_1 C_1$
I	Improved rice seeds	$A_0 I_1 F_0 C_0$, $A_0 I_1 F_1 C_0$, $A_0 I_1 F_0 C_1$, $A_0 I_1 F_1 C_1$	$A_0 I_1 F_0 C_0$, $A_0 I_1 F_0 C_1$, $A_0 I_1 F_1 C_1$
F	Inorganic Fertilizers (NPK and urea)	$A_0 I_0 F_1 C_0$, $A_0 I_0 F_1 C_1$,	$A_0 I_0 F_1 C_0$, $A_0 I_0 F_1 C_1$
C	Crop protection chemicals (Herbicides and Pesticides)	$A_0 I_0 F_0 C_1$	$A_0 I_0 F_0 C_1$

The binary quadruple represents the possible combinations of agricultural technologies and each of the elements in the quadruple is a binary representation of implementing agronomic practices (A), cultivating improved rice seed (I), application of inorganic fertilizers (F), and also application of crop protection chemicals (C). Subscript 1 denotes uptake of the specific category of technology k and 0 denotes otherwise.

The marginal probability (equation 2) which shows the likelihood of utilizing any category of the technologies in k regardless of the others was computed as the sum of the joint probabilities of all the observed combinations of agricultural technologies that contain a specific category of k.

$$pr(k_j) = \sum\left({}^{fd_j}\Big/_{\sum d_n}\right) \tag{2}$$

3.2 Welfare measure of the respondents

3.2.1 Partial factor productivity

The first welfare variable that was computed in this study was the land productivity outcomes of the respondents. This was computed as the volume of harvested paddy rice (Kg) per hectare of farmland cultivated by rice farmers. Following Diskin (1997), the general equation for calculating crop yield per area of farmland cultivated is as shown below:

$$Yield\ (Y) = \frac{total\ output\ (Kg)}{area\ cultivated} \tag{3}$$

3.2.2 Per-capita consumption expenditure (PCE)

The PCE is commonly employed as one of the measures (proxies) of poverty for farming households. Following several studies such as Ngango and Nkurunziza (2021) and Biru *et al.* (2019) amongst others, it was computed as the summation of the monthly food and non-food monetary expenditure (FNFE) in naira per household i, divided by the number of persons n in that household i.

$$PCE_i = \frac{\sum_i FNFE}{n_i} \tag{4}$$

3.2.3 **Poverty probability index (PPI):** following Wossen *et al.* (2017a), and COSA (2016 and 2019), this analytical tool was used to compute the likelihood that a farming household falls below the national poverty line. This PPI is an emerging analytical tool for innovative lean-data techniques. It is a statistically rigorous, yet low-cost and easy-to-administer poverty measurement tool. It shows the percentage of respondents living below a given poverty line based on the answers to 10 country-specific questions about a household's physical living conditions and asset ownership that are derived from national surveys. These questions are available on the PPI website (IPA, 2015). All points in the poverty scorecard are non-negative integers, and total scores range from zero (most likely below a poverty line) to 100 (least likely below a poverty line). The PPI look-up was used to convert a respondent's score to the poverty likelihood values (%) used in the study.

3.3 Instrumental variable probit regression (IV-Probit) model:

The IV-Probit model was employed to examine the factors influencing rice farmers' probabilities of participation in the ABP. Following Wooldridge (2008), and as operationalized by Mulenga *et al.* (2017), the conditional probability of participating in the ABP was explicitly modelled as:

$$pr(S_i = 1) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_{11} X_{11} + \varepsilon_i \tag{5}$$

The dependent variable S_i takes a value of unity for participants and zero otherwise; β_s are unknown parameters to be estimated, X_i denotes a vector of exogenous covariates that are likely to influence the likelihood of participating in ABP (X_I = education of the farmer, X_2 = age of farmer, X_3 = age square, X_4 = sex of the farmer, X_5 = years of rice farming experience, X_6 = income from off-farm work, X_7 = years of residence in present the locality, X_8= social membership, X_9 = crop diversification, X_{10} = production shocks, X_{11} = farmer's location and ε_i = disturbance term. However, the variable X_6 is suspected to be potentially endogenous because it could be correlated with some unobserved variables such as farmers' innate abilities, managerial skills and motivations (captured in the error term ε_i) that are also likely to influence the decision of whether or not to participate in ABP. Thus, this variable may be jointly determined with the decision relating to ABP. Farmers who are actively engaged in off-farm work and earn income from such ventures are less likely to be credit-constrained, and therefore less likely to participate in ABP since the income earned from off-farm work can be used to purchase agricultural inputs that ABP participants receive at subsidized prices. On the flip side, this category of farmers is more likely to qualify as ABP beneficiaries because they can easily provide the minimum upfront cash requirement than paddy rice farmers who are not engaged in off-farm work and hence do not earn off-farm income.

The potential endogeneity of income from non-farm was therefore tested and controlled for using the IV approach which proceeds in two stages. Firstly, non-farm income was specified in the reduced form model as a function of a vector of exogenous covariates X_i from equation (4), plus a valid instrument Z_i that is correlated with X_6 but uncorrelated with the error term:

$$X_6 = \pi X_i + \psi Z_i + \sigma_i \tag{6}$$

Z_i denotes remoteness of farmstead. In this study, Z_i was proxied by distance in Kilometers from farmers' residence to their farmstead. Z_i is an instrument that is partially correlated with the income from non-farm work but uncorrelated with ε_i in equation (5); $\pi\ and\ \psi$ are vectors of unknown parameters to be estimated; while $\sigma_i \sim N(0, \sigma_v^2)$ is the stochastic disturbance term. The distance from farmers' residences to their farmsteads is assumed to be a good instrument because remote farms receive less attention than those with closer proximity. Households living farther from their farmstead have a higher likelihood of also engaging in off-farm ventures within their vicinity to complement the high transaction cost of operating remote farms. According to Manda *et al.* (2015) and Sheahan and Barrette (2014), the remoteness of farmland increases the input and output market transaction cost. Hence, farming households may seek alternative livelihood sources to cushion the effects of such transaction costs. Remoteness of farmstead is likely to be highly correlated with income from non-farm work but less likely to have any direct effect on the decision of whether or not to participate in ABP except through their non-farm income.

The predicted value $\widehat{X_6}_i$ from equation (6) served as an additional covariate in place of the actual non-farm income in equation (5), alongside other covariates from X_i in the final IV-Probit model. The IV-Probit model was therefore implicitly specified as:

$$pr(S_i = 1) = \varrho \widehat{X}_6 + \beta X_i + \varepsilon_i \tag{7}$$

Lastly, thematic analysis was employed to analyse the qualitative data obtained from the Focus Group Discussions (FGDs) with ABP farmers. The results of the thematic analysis were inserted in italicized format to corroborate the preceeding quantitative information obtained via structured questionnaire.

4.0 Results and discussion

4.1 **Joint and marginal probabilities of agricultural technologies uptake among rice farmers**

The joint and marginal probabilities distribution of the various combinations of agricultural technologies utilized by the sampled rice farmers are shown in Table 2. A total of 13 distinct combinations of agricultural technologies were observed for the respondents. The results of the marginal distribution statistics show that rice farming households in the study area are more inclined to apply crop protection chemicals (C_1) and inorganic fertilizers (F_1) than the other agricultural technologies. This affirms the assertion of Sheahan and Barrett (2017) that the application of these technologies in SSA is more extensive than the mainstream assumption about African smallholder agriculture. Approximately 97% of the sampled households applied crop protection chemicals (C_1) to minimize yield loss from weeds and pests. This refutes the allusion of Gianessi and Williams (2011) that the use of herbicides in particular, was an under-exploited means of labour saving and yield enhancement among smallholder farmers. It however corroborates the assertions of Alagbo *et al.* (2022); Mhoja *et al.* (2021); Jiya *et al.* (2019) that chemical weed control represents a pragmatic and economic alternative to labour-intensive hand weeding.

About 50% of the respondents applied inorganic fertilizers (F_1) to enrich their soils and thus, boost rice yields. However, improved rice seeds (I_1) were cultivated by less than one-third of the farming households. This refutes the findings of Mhoja *et al.* (2021). It nevertheless, resonates with the assertions of Ariga *et al.* (2018) and Asfaw *et al.* (2012) that adoption of improved seeds among farmers in SSA is generally low. Furthermore, the results of the thematic analysis provided more insights as recounted by ABP farmers "*We received improved rice seeds (mainly FARO 44 and 45) which increased our output. Some of the respondents from Ekiti State however recounted that the seeds were quite different from the popular varieties (Igbemo rice) grown and consumed within their locales."* This could be the reason for the subsequent low investment in improved rice seeds (I_1) among the respondents.

Less than one-third of the farming households also observed proper agronomic practices (A_1). Since more than 75% of the sampled respondents operated under the upland rice production ecology, this observation reflects the assertion of Takeshima and Bakare (2016) that agronomic practices such as transplanting from nursery and row-planting are less popular in upland rice production ecology, but widely practised in lowland rice production ecology in the bid to minimize the negative effects of erosion and flooding on direct sowing (or broadcasting of rice seeds) in lowlands.

The joint probability statistics also presented in Table 8 show that crop protection chemicals alone ($A_0I_0F_0C_1$) was utilized by about 19% of the respondents. It was combined with inorganic fertilizers ($A_0I_0F_1C_1$) by about 23%, with proper agronomic practices ($A_1I_0F_0C_1$) by approximately 13%, and with improved rice seeds ($A_0I_1F_0C_1$) by approximately 13%. Furthermore, crop protection chemicals were jointly utilized with agronomic practices and inorganic fertilizers ($A_1I_0F_1C_1$) by about 11%, with improved rice seeds and inorganic fertilizers ($A_0I_1F_1C_1$) by about 12% of the respondents. Only about 4% of the households jointly utilized the four categories of agricultural technologies ($A_1I_1F_1C_1$).

The highest proportion of respondents jointly utilized crop protection chemicals and inorganic fertilizers ($A_0I_0F_1C_1$). This is in tandem with the assertion of Kolo *et al.* (2021b) that weed interference and poor soil quality are important factors that contribute to low rice yields in Nigeria. Hence, this distinct mix of agricultural technologies helps to replenish soil nutrients and reduce the negative consequences of weeds on crop yield (Tsinigo and Behrman, 2017).

The application of inorganic fertilizers (F_1) may precipitate the emergence of weeds on farmlands (Sheahan and Barrett, 2017), thus necessitating their joint application with herbicides (C_1). This probably explains why a higher proportion of rice farming households opted for this combination than the other alternatives. Out of the 13 distinct mix of agricultural technologies observed for rice farmers in the study area as shown in Table 8, five (choices 9 to 13) were dropped from further analyses for computational convenience and also because most of them accounted for less than 1% of the total observation.

The joint probability of agricultural technologies uptake was further disaggregated by ABP and non-ABP beneficiary farmers as shown in Table 3. ABP farmers appear to be significantly more likely to opt for choice $A_1I_0F_1C_1$ because a relatively higher percentage of them utilize this combination than their non-ABP counterparts. They are however less likely to opt for choices $A_0I_1F_0C_1$ and $A_0I_0F_0C_1$ because a relatively lower percentage of them utilized these mixes of agricultural technologies than their non-ABP counterparts. Interestingly, there appears to be no statistically significant difference between the technology uptake choices of ABP and non-ABP farmers for the remaining five combinations of agricultural because neither the ABP farmers nor

Table 2: Joint and marginal probabilities of agricultural technologies uptake among rice famers

Choice (j)	Description of choice	Joint Probability (%)	Marginal probability (%) Agronomic practices (A_1)	Improved seeds (I_1)	inorganic fertilizers (F_1)	Crop protection chemicals (C_1)
1	$A_1 I_1 F_1 C_1$ (households that utilize all four categories of technologies)	3.79	3.79	3.79	3.79	3.79
2	$A_1 I_0 F_1 C_1$ (agronomic practices, inorganic fertilizers and crop protection chemicals)	10.50	10.50	-	10.50	10.50
3	$A_1 I_1 F_0 C_1$ (agronomic practices, improved rice seeds, and crop protection chemicals)	2.41	2.41	2.41	-	2.41
4	$A_0 I_1 F_1 C_1$ (improved rice seeds, inorganic fertilizers and crop protection chemicals)	12.05	-	12.05	12.05	12.05
5	$A_0 I_1 F_0 C_1$ (improved rice seeds and crop protection chemicals)	12.74	-	12.74	-	12.74
6	$A_1 I_0 F_0 C_1$ (agronomic practices and crop protection chemicals)	13.25	13.25	-	-	13.25
7	$A_0 I_0 F_1 C_1$ (inorganic fertilizers and crop protection chemicals)	22.72	-	-	22.72	22.72
8	$A_0 I_0 F_0 C_1$ (crop protection chemicals only)	19.45	-	-	-	19.45
9	$A_1 I_0 F_0 C_0$ (agronomic practices only)	1.03	1.03	-	-	-
10	$A_0 I_0 F_1 C_0$ (inorganic fertilizers only	0.86	-	-	0.86	-
11	$A_1 I_0 F_1 C_0$ (Agronomic practices and inorganic fertilizers)	0.52	0.52	-	0.52	-
12	$A_0 I_1 F_0 C_0$ (improved rice seeds only)	0.52	-	0.52	-	-
13	$A_1 I_1 F_0 C_0$ (agronomic practices and improved seeds)	0.17	0.17	0.17	-	-
	Total	**100**	**31.67**	**31.68**	**50.44**	**96.91**
	Number of observations			581		

$j = 1, \ldots, 13$ denote the observed combinations of agricultural technologies. Each component in the quadruple is a binary variable for technology uptake: agronomic practices (A), improved rice seed (I), inorganic fertilizers (F) and crop protection chemicals (C). Subscript 1 denotes uptake of the specific technology and 0 denotes otherwise.

Source: Field survey data, 2023

their non-ABP counterparts were significantly more or less inclined to utilize these combinations of agricultural technologies. These findings suggest that participation in the ABP did not significantly incentivize rice farmers in their technology uptake decisions. Hence, we fail to reject null hypothesis one (H_{01}) for this study. The results of the thematic analysis provided some insights as to the possible reasons for this finding as recounted by ABP farmers "*Some of us received training on the use of agrochemicals, irrigation, crop spacing, cultivating improved rice, entrepreneurship and insuring our farms. Some however reported that no training was conducted for their cluster groups, while others further recounted that trainings were conducted for their leaders only, thus excluding them.*" Those who received training reported that "*we were not able to implement some of the trainings because there were no facilities to do so. For instance, irrigation facilities for upland production and also farm machinery for land preparation were not available though some of us were educated on the benefits of these technologies.*" Others further claimed that "*we were given fake/expired agrochemicals that were not beneficial to us.*" Resource constraints issues therefore persisted among ABP rice farmers, just as it is typical among marginalized smallholder farmers.

Table 3. Joint probabilities of technology uptake among ABP and non-ABP farmers

Choice (*j*)	Description of *j*	Percent of ABP farmers	Percent of Non-ABP farmers	Mean difference
1	$A_1 I_1 F_1 C_1$	4.64	2.75	1.89
2	$A_1 I_0 F_1 C_1$	15.07	4.13	10.83***
3	$A_1 I_1 F_0 C_1$	2.61	2.30	0.32
4	$A_0 I_1 F_1 C_1$	11.88	13.30	-1.42
5	$A_0 I_1 F_0 C_1$	8.99	19.72	-10.74***
6	$A_1 I_0 F_0 C_1$	15.07	11.47	3.60
7	$A_0 I_0 F_1 C_1$	24.64	21.56	0.31
8	$A_0 I_0 F_0 C_1$	17.10	24.77	-7.67**
	Number of observations		563	

Statistical significance at ***p<0.01 and **p<0.05 from independent samples t-test
Source: Field survey data, 2023

4.2 **Characteristics of the respondents disaggregated by their technology uptake choices**

Following Kankwamba and Mangisoni (2015), the summary statistics of the respondents' socioeconomic and other farm-level characteristics disaggregated by their choices of agricultural

Table 4: Descriptive statistics of the respondents by their agricultural technology uptake choices

Covariates	Technology uptake choices $A_1 I_1 F_1 C_1$	$A_1 I_0 F_1 C_1$	$A_1 I_1 F_0 C_1$	$A_0 I_1 F_1 C_1$	$A_0 I_1 F_0 C_1$	$A_1 I_0 F_0 C_1$	$A_0 I_0 F_1 C_1$	$A_0 I_0 F_0 C_1$	Mean	Test stat.	Sig.
Socioeconomic characteristics											
Years of formal education	10.50	9.28	11.43	9.50	10.32	9.55	9.66	8.42	9.50	1.84	
Age of farmer	51	49	44	50	45	48	47	46	48	2.73	***
Sex of farmer (Male =1)	0.73	0.77	0.80	0.80	0.76	0.81	0.7	0.73	0.75	4.63	
Years of residence in the locality	28.59	31.54	30.29	32.59	30.95	32.62	27.80	35.37	31.48	2.40	**
Rice farming experience (years)	18.77	18.54	15.21	18.95	16.64	21.62	15.00	15.19	17.19	3.52	***
Off-farm income (₦)	16363.64	32540.98	11785.71	12871.43	20783.78	15454.55	21117.42	15451.33	18956.48	3.00	***
Social group membership (membership of social group =1)	1.00	0.82	0.71	0.70	0.76	0.76	0.79	0.77	0.79	16.48	**
Farm-level characteristics											
Farmer's location (Ekiti State = 1; Ogun State = 0)	0.5	0.31	0.64	0.51	0.86	0.30	0.36	0.67	0.51	84.91	***
Production shocks (if a farmer experienced drought, flood, pest and disease outbreak in the last three years =1; otherwise = 0)	0.82	0.70	0.86	0.80	0.84	0.78	0.59	0.73	0.73	22.32	***
Crop diversification (if a farmer cultivates other crops besides rice = 1; otherwise = 0)	0.64	0.62	0.85	0.64	0.82	0.62	0.58	0.64	0.65	16.28	**
Rice production ecology (upland=1; lowland =0)	0.55	0.77	0.43	0.80	0.46	0.86	0.91	0.77	0.76	72.01	***
Instrumental variable											
Distance to farmstead (Km)	2.92	3.42	4.25	3.89	3.55	4.08	5.01	3.93	4.06	3.66	***

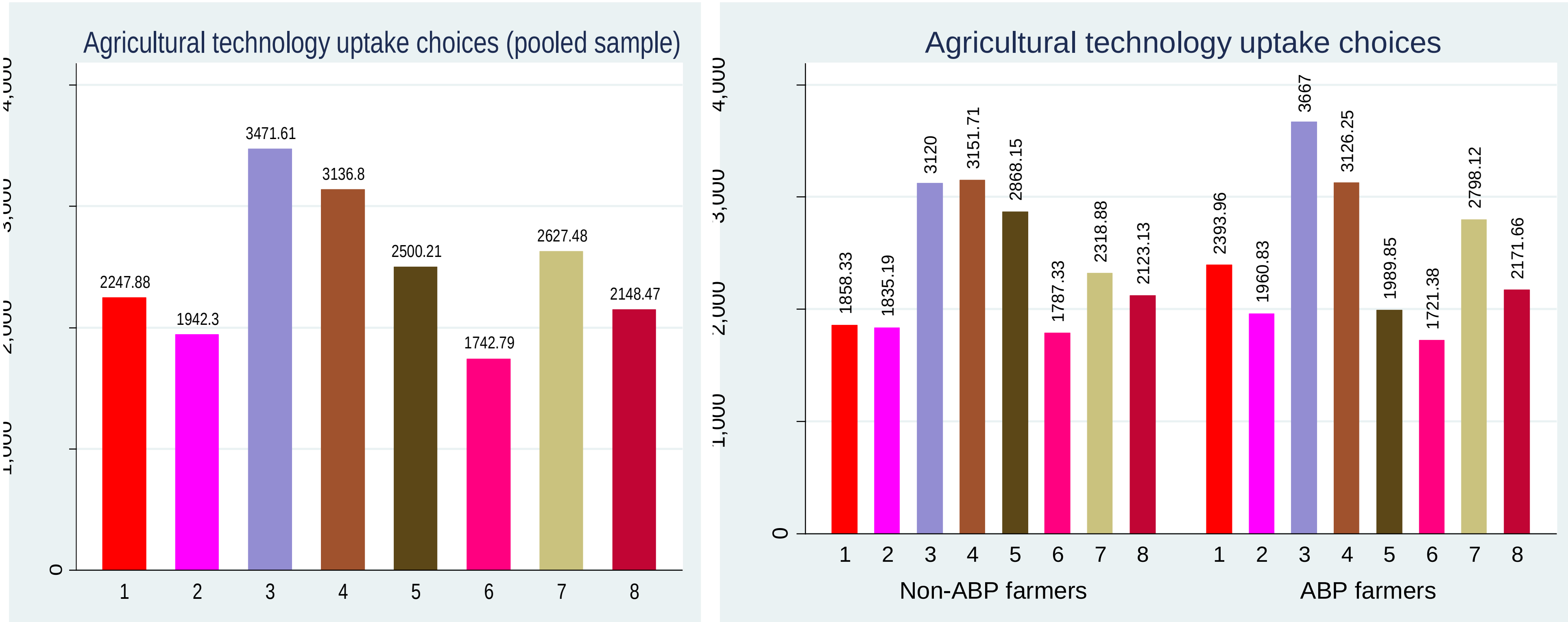
F-test and chi-square are used for continuous and categorical variables, respectively. Statistical significance **p<0.05, ***p<0.01. N= 563 technologies are shown in Table 4. The Analysis of Variance (ANOVA) and Pearson's chi2 techniques were employed to test for statistical significance among the continuous and categorical variables respectively. The results indicate that the most of the socioeconomic and farm-level characteristics of the respondents are systematically different across the various combinations of agricultural technologies utilized. That is, the sampled rice farmers are markedly different in several observed individual characteristics across the various mix of technologies opted for. However, with respect to their educational attainment, there is no statistically significant difference in the number of years sampled farmers that opted for different combinations of agricultural technologies spent schooling. Also, with respect to the sex of the farmers, the male folks dominated the sampled respondents and as expected, they are not statistically significant across the various mix of technologies opted for. We proceeded further to investigate if their welfare outcomes differ contingent on the observed mix of agricultural technologies utilized.

4.3 Analysis of the welfare outcomes of rice farming households contingent their technology uptake choices

4.3.1 ***Rice productivity***

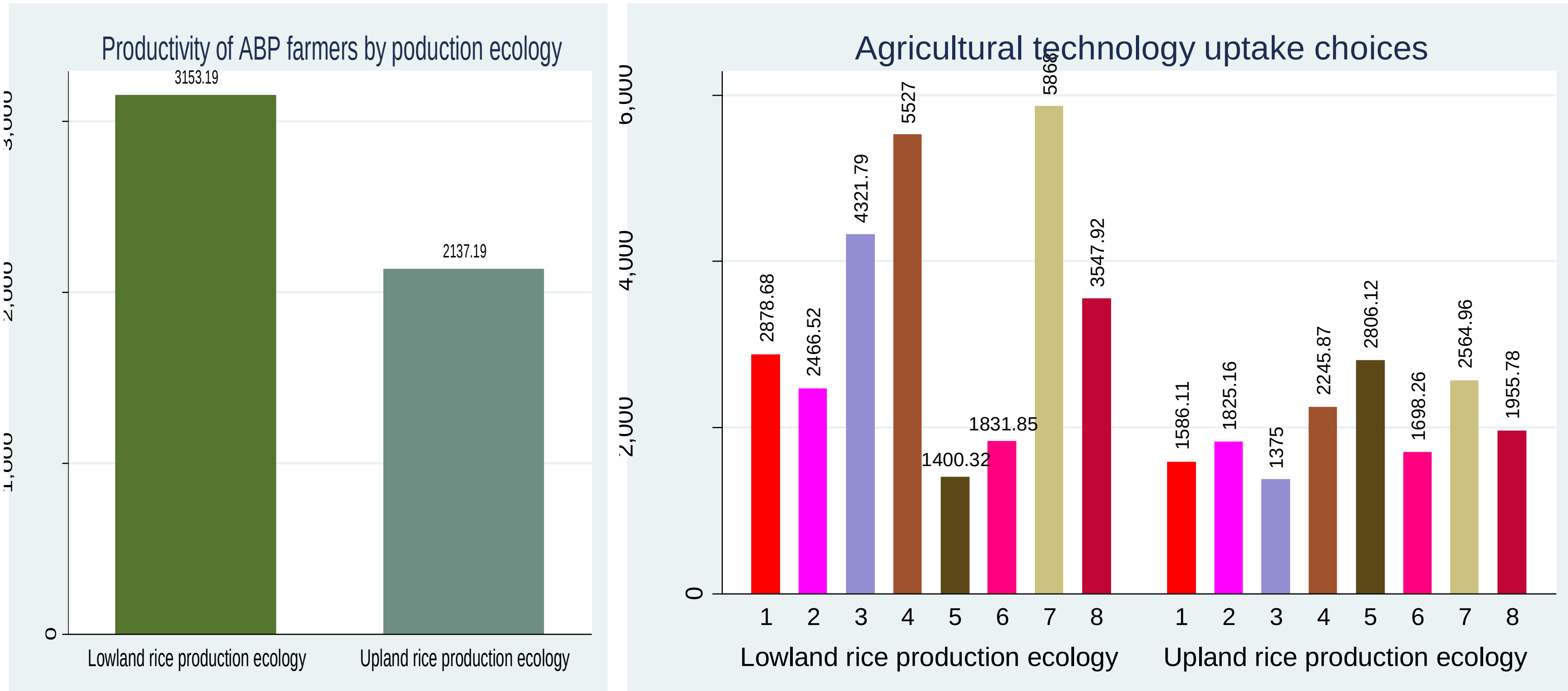
The results of the partial productivity analysis (rice output per hectare of farmland) are shown in Figures 1 and 2. As graphically illustrated in panel A of Figure 4, farmers who utilized different combinations of agricultural technologies do not have the same rice yield per hectare. A one-way Analysis of Variance (ANOVA) was conducted to determine if the observed productivity outcomes varied significantly for farmers contingent on their technology uptake choices. The results indicated that there were statistically significant differences $[F(7, 555) = 3.25, p = 0.00]$ in the rice yield per hectare of farmers who opted for different combinations of agricultural technologies. A Tukey's test post estimate revealed that productivity was significantly higher for households who utilized choice $A_0I_1F_1C_1$ than those who opted for choice $A_1I_0F_0C_1$.

Upon further disaggregation by ABP and non-ABP beneficiary farmers, as shown in panel B of Figure 1, it was observed that ABP and non-ABP farmers who utilized similar combinations of agricultural technologies had dissimilar rice productivity outcomes. ABP rice farmers that utilized choices 1 ($A_1I_1F_1C_1$), 2 ($A_1I_0F_1C_1$), 3 ($A_1I_1F_0C_1$), 7 ($AI_0F_1C_1$) and 8 ($A_0I_0F_0C_1$) appear to have



Panel A Panel B

Figure 1: Productivity of rice farmers disaggregated by their technology uptake choices



Panel A Panel B

Figure 2: Productivity of ABP farmers by rice production ecologies

Source: Field survey data, 2023

higher productivity outcomes than their non-ABP counterparts. The results of the one-way ANOVA indicated that there were significant differences $[F(7, 337) = 2.40, p = 0.02]$ in the productivity of ABP farmers based on their technology uptake choices. The Tukey's test that was post-estimated revealed that a negligibly significant difference existed between the productivity of ABP farmers who opted for choice 4 ($A_0I_1F_1C_1$) and those who opted for choice 6 ($A_1I_0F_0C_1$).

The average productivity of ABP rice farmers in the study area was 2372.78 Kg per hectare. Although this value is a bit higher than the national average of 2297.4 Kg/ha reported by USDA-FAS (2022), it is however less than what was reported for ABP farmers in Kwara and Kebbi States, in Northern Nigeria (Ayinde *et al.*, 2019; Kara *et al.*, 2019) were rice is predominantly cultivated in the irrigated lowland production ecology.

The results of the thematic analysis provided insight into the resource constraint issues confronting the respondents concerning their rice production ecologies. "*Although some of the farmers admitted that they were given water pumps and hose, they were however not sufficiently empowered to use irrigation facilities and water scarcity was a major challenge reported by most of them".* Hence, the productivity of ABP rice farmers was further disaggregated by the rice production ecologies under which the farmers operated.

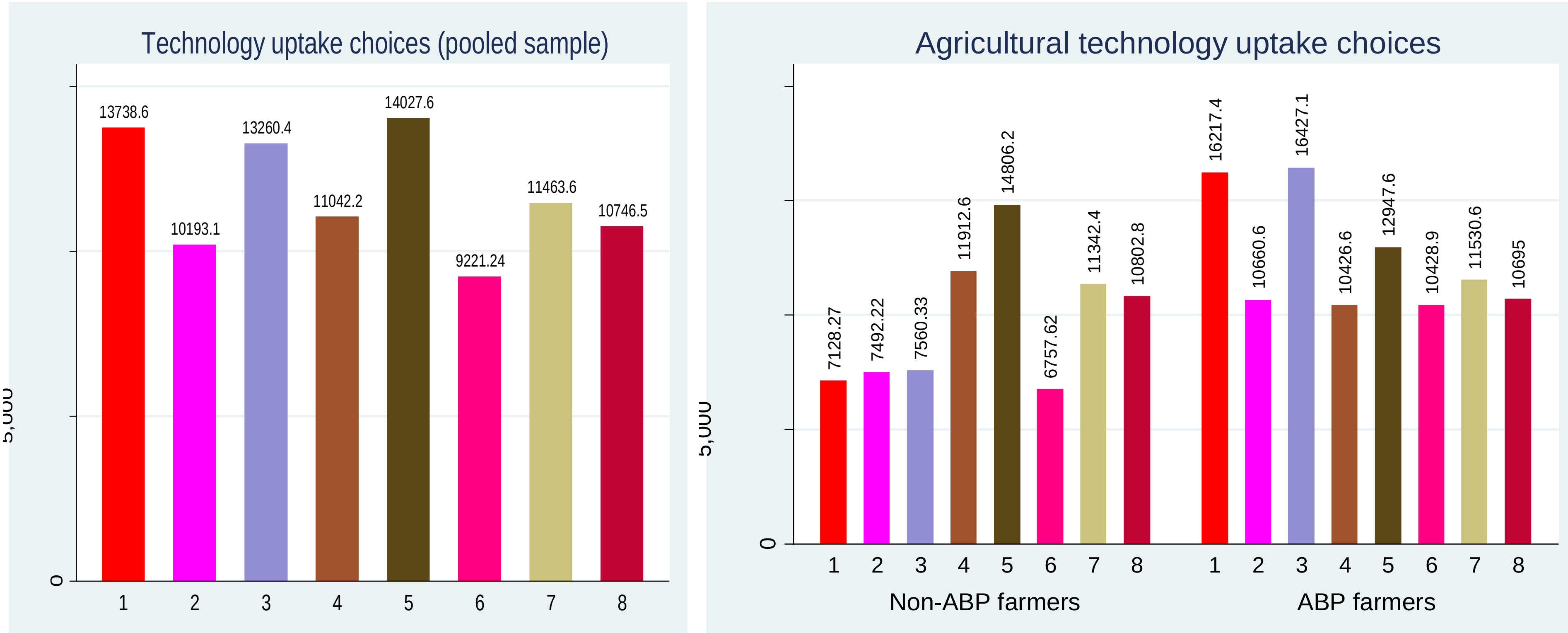
The illustrations in panel A of Figure 2 show that farmers who cultivated rice under the dominant rain-fed upland production ecology had significantly lower average yield per hectare than the minority who cultivated rice in the rain-fed lowland production ecology. Several studies including Erenstein *et al.*, (2003); Longtau, (2003); Takeshima and Bakare, (2016) have documented similar findings for rice yields across Nigeria. The results of the one-way ANOVA indicated that there was no statistically significant difference $[F(7, 265) = 1.59, p = 0.14]$ in the rice productivity of farmers operating under the dominant upland production ecology based on their technologies uptake choices. However, for the minority operating under the lowland production ecology, there was a statistically significant difference $[F(7, 80) = 2.60, p = 0.02]$ in their rice productivity based on their technology uptake choices. A Tukey's test that was post-estimated revealed that ABP farmers who opted for choice 4 ($A_0I_1F_1C_1$) had significantly higher rice productivity than those who opted for choice 5 ($A_0I_1F_0C_1$).

4.3.2 ***Per capita consumption expenditure (PCE)***

The results of the computed PCE which is the second welfare outcome considered in this study are shown in Figures 3 and 4. As depicted in panel A of Figure 3 which shows the results for the pooled sample, households who utilized different combinations of agricultural technologies do not have the same PCE. A one-way Analysis of Variance (ANOVA) was conducted to determine if the observed PCE outcomes varied significantly for households contingent on their technology uptake choices. The results indicated that there were statistically significant differences in the PCE $[F(7, 555) = 2.27, p = 0.03]$ of farming households who opted for different combinations of agricultural technologies. A Tukey's test that was post-estimated revealed that the PCE was significantly higher for households who utilized choice 5 ($A_0I_1F_0C_1$) than those who opted for choice 6 ($A_1I_0F_0C_1$).

Upon further disaggregation by ABP and non-ABP beneficiary farmers, as shown in panel B of Figure 3, it was observed that ABP and non-ABP farmers who utilized similar combinations of agricultural technologies appeared to have dissimilar PCE outcomes. A higher consumption expenditure was observed for ABP farming households across the various mix of agricultural technologies. The results of the one-way ANOVA indicated that the relatively higher PCE outcomes of ABP farming households were statistically similar $[F(7, 337) = 1.42, p = 0.20]$ across the various mix of agricultural technologies utilized by the beneficiary farmers.

The illustrations in panel A of Figure 4 show that farming households that cultivated rice under the dominant rain-fed upland production ecology had lower PCE than the minority who cultivated rice in the rain-fed lowland production ecology. The results of the one-way ANOVA indicated that there is statistically significant difference $[F(7, 257) = 2.35, p = 0.03]$ in the PCE of farming households operating under the dominant upland production ecology based on their technologies uptake choices. A Tukey's test that was post-estimated revealed that ABP farmers who opted for choice 7 ($A_0I_0F_1C_1$) had significantly higher PCE than those who opted for choice 4 ($A_0I_1F_1C_1$). However, for the minority operating under the lowland production ecology, there was no statistically significant difference $[F(7, 72) = 1.07, p = 0.39]$ in their relatively higher PCE based on their technology uptake choices.



Panel A Panel B

Figure 3: PCE of farming households disaggregated by their technology uptake choices
Source: Field survey data, 2023

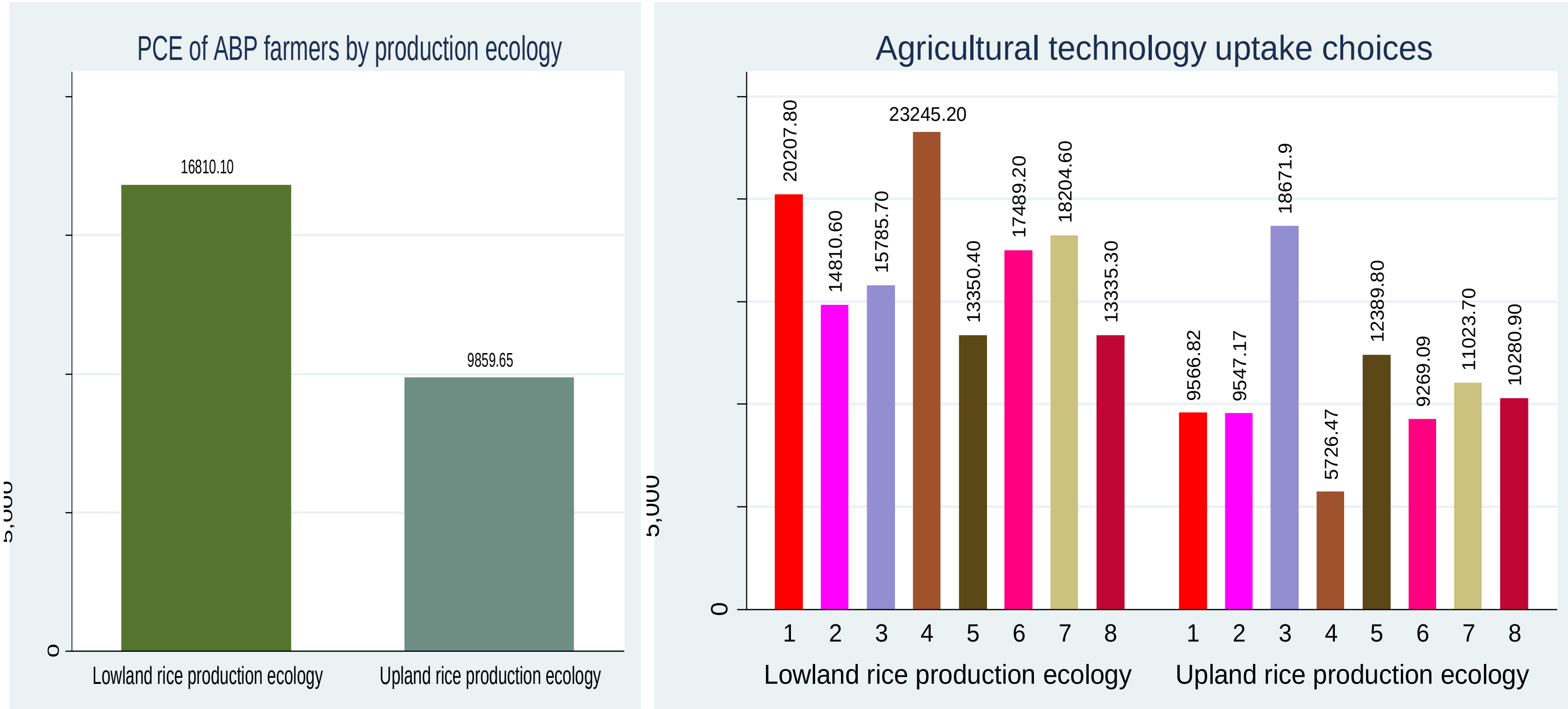


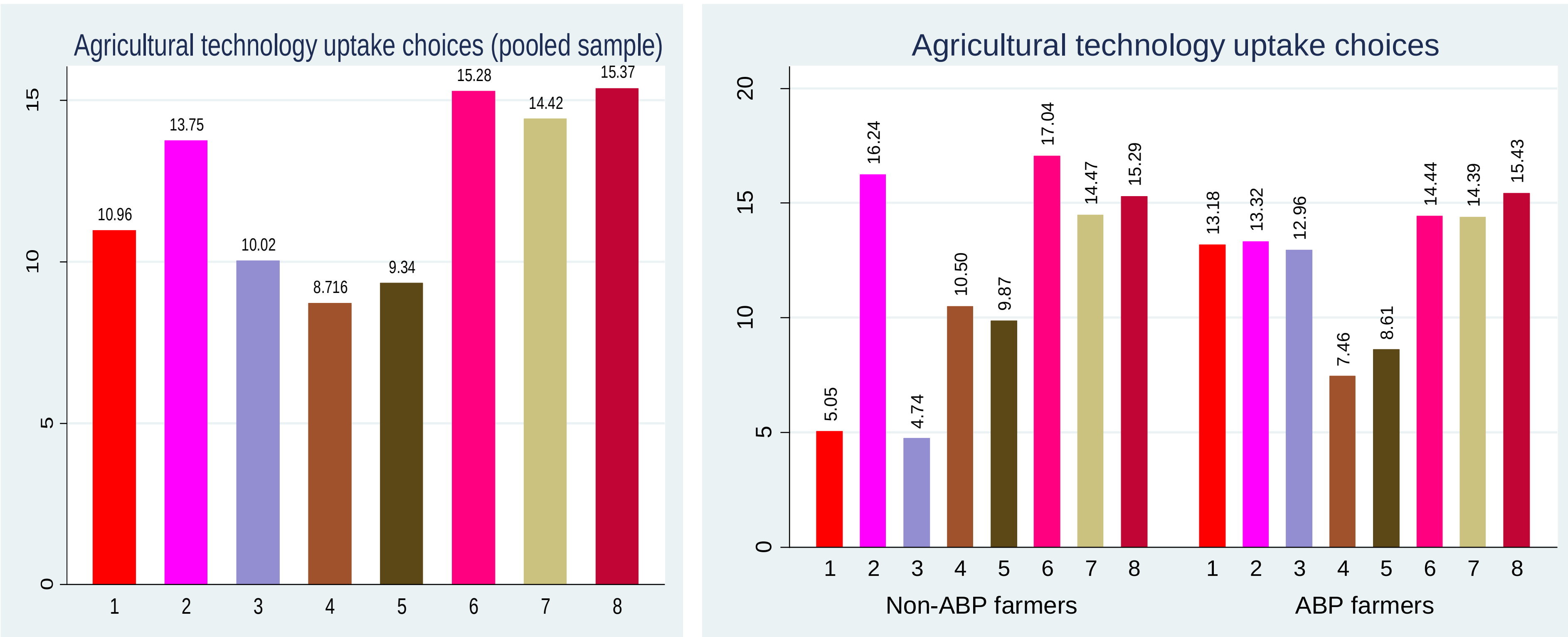
Figure 4: Per capita consumption expenditure of ABP farming households by rice production ecologies
Source: Field survey data, 2023

4.3.3 ***Poverty likelihoods***

As graphed in panel A of Figure 5 which shows the results for the pooled sample, households who utilized different combinations of agricultural technologies do not have the same likelihood of having consumption expenditures that are below the national poverty line. A one-way ANOVA was conducted to determine if the observed poverty likelihood outcomes varied significantly for households contingent on their technology uptake choices. The results indicated that there were statistically significant differences in the poverty likelihood $[F(7, 555) = 3.01, p = 0.00]$ of farming households who opted for different combinations of agricultural technologies. A Tukey's test post estimated revealed that households who utilized choice 8 ($A_0I_0F_0C_1$) had higher likelihoods of having consumption expenditures that are below the national poverty line than those who opted for choice 4 ($A_0I_1F_1C_1$).

Upon further disaggregation by ABP and non-ABP beneficiary farmers, as shown in panel B of Figure 5, ABP farmers did not appear to fare better than their non-ABP counterparts across most of the mix of agricultural technologies. Nonetheless, those who opted for choices 4 ($A_0I_1F_1C_1$), 5 ($A_0I_1F_0C_1$) and 6 ($A_1I_0F_0C_1$) appear to have relatively lower likelihoods of having consumption expenditures that are below the national poverty line. The results of the one-way ANOVA indicated that the poverty likelihoods of ABP farming households were statistically similar $[F(7, 337) = 1.95, p = 0.06]$ across the various mix of agricultural technologies utilized.

The illustrations in panel A of Figure 6 show that farming households that cultivated rice under the dominant rain-fed upland production ecology appear to have similar poverty likelihoods with those in the minority who cultivated rice in the rain-fed lowland production ecology. The results of the one-way ANOVA indicated that there is no statistically significant difference $[F(7, 257) = 1.24, p = 0.28]$ in the poverty likelihoods of farming households operating under the dominant upland rice production ecology based on their technologies uptake choices. A similar finding $[F(7, 72) = 1.57, p = 0.16]$ was also reported in the minority who operated under the lowland rice production ecology.



Panel A

Panel B

Figure 8: Poverty likelihood distribution by technology uptake choices (Panel A) and ABP status/technology uptake choices (Panel B)

Source: Field survey data, 2023

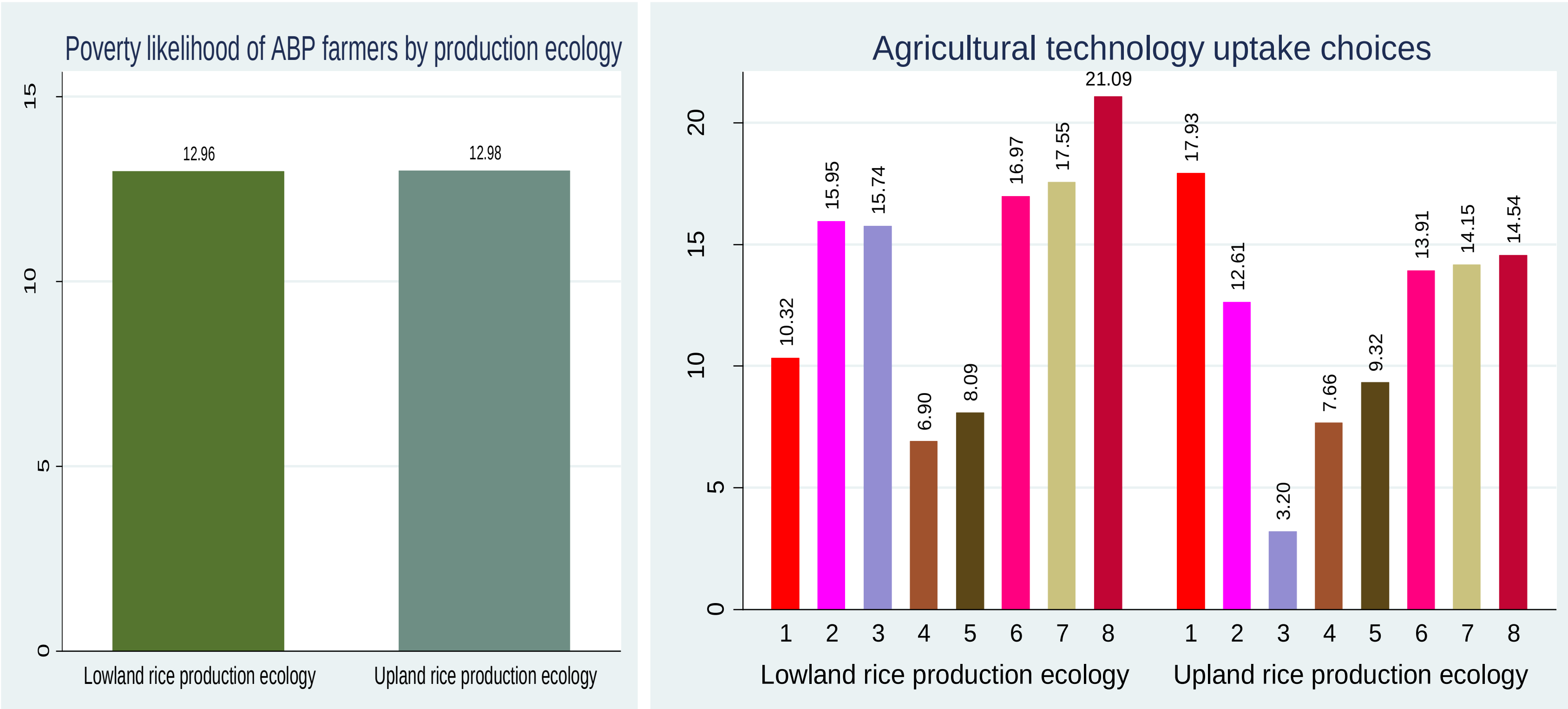


Figure 9: Poverty likelihoods of ABP farming households by rice production ecologies
Source: Field survey data, 2023

4.4 **Analysis of factors influencing participation in the ABP**

Table 5 shows the estimates of the IV-Probit model that was used to analyze the factors influencing the decision to participate in the ABP. Column A shows the results of the reduced-form OLS model for non-farm income (primarily to highlight the relevance of the instrument), while column B is the second stage main results from the IV-Probit model.

The statistical test using the F-statistics from the first stage OLS equation was 11.43 which is higher than the threshold of 10 provided by Stock and Watson (2003) as a rule of thumb to determine the relevance of an instrument. Thus, indicating that the remoteness of the farmstead is not a weak instrument, and the subsequent tests of significance (z-tests) based on the IV-Probit estimates are reliable. As earlier hypothesized, the results of the reduced-form model show that the distance to farmstead is significantly correlated with off-farm income. Households with farms that are farther from their homes have higher off-farm incomes. According to Teklewold *et al.* (2013b), farms that are further away receive less attention and monitoring. Thus, freeing up time for farming households to engage in off-farm livelihood activities with lower opportunity costs within their vicinity.

For the main IV-Probit model, the result of the Wald test of exogeneity of the instrumented variable (correlation = 0) provides sufficient evidence of the suspected endogeneity of off-farm income, thus, the aptness of the IV-Probit model in addressing this endogeneity problem. Also, the significance of the Wald Chi-Square test statistic [chi2(11)] enables us to reject the null hypothesis that the partial slope coefficients in the IV-Probit model are simultaneously equal to zero. The results of the marginal effects which show the change in the probability of participating in the ABP emanating from a change in any of the covariates *ceteris paribus* are reported. The results show that farmers who earn higher income from non-farm livelihood activities were about 11 percentage points less likely to participate in the ABP. This corroborates the earlier assertion that farmers who are actively engaged in off-farm work and earn more income from such ventures are less likely to be credit-constrained, and therefore less likely to participate in ABP since the income earned from off-farm work can be used to purchase agricultural inputs that ABP participants receive at subsidized prices. Bhata *et al.* (2019) reported similar findings for South African farmers who participated in an agricultural intervention programme. The result of the thematic analysis provided further insights as the ABP farmers recounted “*We decided to register because they promised to subsidize inputs for us and buy our products at an agreed price. We registered with the hope that the government has come to assist us. We felt our suffering has ended and we were happy to hear that the government was set to provide inputs and cash for rice farmers.*”

Farmers with more years of formal education are more likely to participate in ABP than those with fewer years of education. An additional year of formal education increases the probability of participating in the ABP by two percentage points. This corroborates the findings of Bidzakin *et al.* (2019); Bhata *et al.* (2018); Jena *et al.* (2015). It however contradicts the findings of Parvanti and Waibel (2015) and Abdulai and Al-hassan (2016).

Rice farmers who are members of social groups are about 38 percentage points more likely to participate in the ABP than non-members. Olarenwaju *et al.* (2021) reported similar findings for ABP rice farmers in Kaduna State Nigeria. Also, Davis *et al.* (2010) reported similar findings for East African farmers. Farmers who cultivate other crops besides rice are about 22 percentage points less likely to participate in the ABP. This finding resonates with the result reported earlier that households whose income depends significantly on rice production are more inclined to participate in the ABP. Since the ABP requires farmers producing any of its listed priority agricultural commodities to form clusters and pool the resources needed to receive subsidized inputs, it seems intuitive for specialized rice farmers to be more inclined to participate in the programme.

5.0 Summary of findings and conclusion

This study provided empirical evidence that participation in the ABP did not significantly incentivize agricultural technology utilization among beneficiary rice farmers. Generally, the welfare outcomes of rice farmers appear to differ contingent on their technology uptake choices. ABP and non-ABP farmers who utilized similar combinations of agricultural technologies had different welfare outcomes. Since the productivity of ABP farmers appears to be negligibly different across the various mix of agricultural technologies, it is not surprising that their poverty outcomes are statistically similar regardless of their technology uptake choices, save for the PCE of those that cultivated rice in the upland production ecology.

Table 5: Parameter estimates of the factors influencing participation in the ABP

Variables	Column A Reduced-form model (Net farm income)	Column B IV-Probit model		
	Coefficients	Coefficients	P>|z|	Marginal effects
Socioeconomic characteristics				
$Non - \widehat{farm}\ income$		-0.17*** (0.03)	0.00	-0.11
Education of farmer	0.07 (0.05)	0.04** (0.01)	0.01	0.02
Age of farmer	-3.12** (1.33)	-0.02 (0.04)	0.68	-0.01
Age square	0.02 (0.01)	-0.00 (0.00)	0.99	-0.00
Sex of farmer	-2.61*** (0.48)	-0.32* (0.17)	0.06	-0.20
Rice farming experience	-0.06** (0.02)	-0.01 (0.01)	0.16	-0.01
Years of residence in locality	0.05** (0.02)	0.01** (0.00)	0.03	0.01
Social group membership	0.61 (0.51)	0.62***(0.20)	0.00	0.38
Farm characteristics				
Crop diversification	-1.29*** (0.44)	-0.35*** (0.11)	0.00	-0.22
Production shocks	-1.27** (0.55)	-0.16 (0.15)	0.30	-0.10
Farmer's location	0.14 (0.58)	-0.14 (0.14)	0.31	-0.09
Remoteness of farm	0.20*** (0.08)			
Constant	15.92*** (3.26)	1.45 (1.33)	0.28	
Diagnostic statistics				
F (11, 551)	11.43***			
Wald chi2(11)		260.27***		
Wald test of exogeneity (correlation = 0) : chi2(1)		7.82**		
Number of observations		563		

The figures in parenthesis are the standard errors. Statistical significance * P < 0.1, ** P < 0.05, *** P < 0.01
Source: Field survey data, 2023

While social group membership is the strongest determinant of rice farmers' probability of participating in the ABP, diversification of cropping activities is the strongest encumbrance. Although rice farmers tend to favour the application of agrochemicals, especially crop protection chemicals, they however appear to be averse to cultivating improved rice seeds and implementing proper agronomic practices. Therefore, it is recommended that improved rice seeds with greater resistance to weeds/pests interference as well as proper agronomic practices that improve the efficiency of the existing weeds/pest control technologies should spearhead future developmental solutions to improving rice productivity in the policy space in Nigeria. Also, informal social institutions such as farmers' groups should be strongly advocated by relevant stakeholders and constitutionally strengthened as a means of improving the social capital base and livelihood outcomes of resource-constrained smallholder farmers in Nigeria.

Acknowledgement

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