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maujan@alparslan.edu.tr
maujan.alparslan.edu.tr

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Adoption potentials of Urea Deep Placement (UDP) technology among smallholder rice farmers in Kano state of Nigeria

Sanusi Mohammed Sadiq [1]✉ • Invinder Paul Singh [2] • Muhd. Makarfi Ahmad [3] • Mahmud Sarki [4]

[1] Department of Agricultural Economics and Extension, FUD, Dutse, Nigeria
[2] Department of Agricultural Economics, SKRAU, Bikaner, India
[3] Department of Agricultural Economics and Extension, BUK, Kano, Nigeria
[4] Department of Education, FUD, Dutse, Nigeria

✉ Corresponding Author: sadiqsanusi30@gmail.com

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A B S T R A C T

Urea deep placement (UDP) technology, a package introduced by USAID MARKETS II is challenged with limited scope in adoption and diffusion, thus the need to investigate the obstacles affecting its adoption potential in the studied area. A cross sectional data elicited through a well-structured questionnaire coupled with interview schedule from a sample size of 300 respondents: adopters (192) and non-adopters (108) sampled via multi-stage sampling technique was used. The collected data were analyzed using Heckman's model, Treatment effect model and Oaxaca-Blinder decomposition model. From the empirical findings it was established that improved seed varieties simultaneously influenced the adoption level and use-intensity of UDP technology. Further, it was found that knowledge awareness on the technology through USAID MARKET II, promoters of the technology, had significant impact on the adoption rate of the technology. However, the potential adoption rate was hampered due to incomplete diffusion, thus created a gap that hovers around 36.85-43.33%. Also, it was established that interaction effect on one hand- threefold decomposition and adoption discrimination effect termed project effect on the other hand- twofold decomposition were the major determinants of yield gap between the adopters and non-adopters. Generally, it was concluded that the prospect of the technology is very bright in the studied area. Consequently, the study recommends that the promoter of the project should adopt an effective cost approach i.e. farmer-to-farmer extension approach in scaling-up the rate of adoption of the UDP technology which exhibited a promising prospect in the studied area.

1. INTRODUCTION

For nearly four decades, several African countries have been modernizing their agricultural sectors in order to ensure strong, long-term economic growth, food security, and poverty reduction. Sadly, agricultural expansion has not been sufficient to alleviate poverty, assure food security, or generate long-term economic growth (Kinuthia and Mabaya, 2017). Governments and development groups have long pushed agricultural technologies as viable means to boost farm output and decrease poverty (Ruzzante et al., 2021).

Increased agricultural productivity through the adoption, diffusion of improved agricultural technologies and practices has been considered as one of the viable means of achieving economic growth and agricultural transformation in low-income countries in the face of natural resource scarcity and climate uncertainty (Kumar et al., 2020). However, many ostensibly beneficial technologies are nonetheless underutilized (Ruzzante et al., 2021). Adoption of a broad mix of such technologies and practices is often required to meet the multifaceted goals of efficiency, profitability, environmental sustainability, and climate resilience (Kumar et al., 2020).

The development and dissemination of revolutionary agricultural technology is seen as a way to enhance output on the world's 475 million small farms (less than 2 hectares), many of which are found in low- and middle-income countries (Lowder et al., 2016). Agriculture's responsible growth, according to most development experts, is a critical component in achieving, at the very least, sustainable development goals. 1 (no poverty), 2 (zero hunger), 3 (excellent health and well-being), 10 (reduced inequalities), 12 (responsible consumption and production), 13 (climate action), 14 (life below water), and 15 (life on land) are the goals.

Since the mid-twentieth century, the international community has substantially invested in the development of technology that increases yields, limit exposure to environmental shocks, produce more nutritious crops, reduces human labor requirements, and promotes long-term sustainability (Pardey et al., 2016a). According to evaluations of this investment, there was a very efficient use of public funds (Pardeyet al., 2016a). Aggregate estimates of agricultural research effectiveness; however, conceal a great deal of heterogeneity: a few initiatives drive the average up, while many others fail (Pardey et al., 2016b). A high number of people adopting a new technology is a necessary (but not sufficient) condition for it to make an impact.

Because the vast majority of the world's poor live in rural areas and work in agriculture, attempts to reduce their vulnerability frequently focus on improving agricultural techniques as a means of increasing production, efficiency, and, eventually, income (Parvan, 2011; Zaidi and Munir, 2014). The introduction of new agricultural technology appears to bring a significant rise in output and income (Zaidi and Munir, 2014).

Rural poverty and productivity shortages in developing countries, particularly in Sub-Saharan Africa (SSA), are largely explained by the slow adoption of modern agricultural technologies (Hörner et al., 2022). Poor soil fertility induced by land degradation is one of the causes of low agricultural output in Sub-Saharan Africa. As a result, in many countries, food insecurity and poverty have become the norm. Nonetheless, in order to improve the soil fertility of Africa's arable regions, particularly Nigeria, agricultural innovations such as mineral fertilizer must be researched (Donkoret al., 2019).

One of the main goals of Nigerian agricultural development plans and strategies is to transition from low-productivity subsistence agriculture to a high-productivity agro-industrial economy. That is, moving away from old production practices and toward new, science-based production methods that involve new technical components and/or perhaps entire farming systems (Hassen, 2014).

Smallholder's adoption of new agricultural technologies is seen as the most important avenue out of poverty. Adoption, if done effectively, should boost productivity and offer more cash to farmers. In this sense, technology adoption can help millions of farmers escape poverty by accelerating economic growth and creating marketing opportunities. Better agricultural technology acceptance rates, on the other hand, have been disappointing and far from complete, and identifying the fundamental barriers to adoption remains a challenge (Wossen et al., 2015; Wossen et al., 2017). Adoption of new agricultural technologies is essential for the transition to a more sustainable farming system, as well as a driving factor for increasing agricultural output (Obayelu et al., 2016).

Rice productivity should be raised to fulfill the expanding population's food need, while also taking into account the shrinking amount of land accessible for farming. This necessitates the careful application of agricultural inputs, such as high-quality seeds and fertilizers, as well as irrigation water management and other best agricultural practices (Islam et al., 2018). The most significant practices in rice production are fertilizer application and water control. Although nitrogen fertilizer is important in rice cultivation, all fertilizers should be used in a balanced manner to improve crop output and soil fertility.

The cost of nitrogen fertilizer in rice production accounts for up to one-third of the entire production costs. It is inefficient to apply it as granules since only approximately one-third of the nitrogen is used up and the rest is lost. Forming Urea into "Briquettes" and placing them deeply in the soil is one way to reduce nitrogen losses and improve fertilizer efficiency. This IFDC (International Centre for Soil Fertility and Agricultural Development)-developed technique is currently widely used in Asia and is being extended into Africa. Urea has risen to prominence as a key nitrogen fertilizer for rice production, with data indicating that about 80% of urea is used in rice production (Hoque et al., 2013).

When compared to the broadcast method, deep placement of all needed fertilizers may be more efficient and farmers may benefit more. In addition, urea deep placement (UDP) enhances nitrogen utilization efficiency (NUE) by up to 80% (Huda et al., 2016). As a result, when compared to broadcast, UDP in rice production reduces nitrogen fertilizer requirements by 30-35 percent while increasing grain yields by up to 15-20 percent. In nations where nitrogen fertilizer subsidies exist, UDP minimizes government subsidy payments in addition to increasing farm profitability (Miah et al., 2016; Islam et al., 2018). As a result of the better nitrogen "uptake" efficiency given by the bigger urea particle size and the "point placement" mode of administration, the adoption of UDP technology has two key benefits: increased yields and decreased fertilizer costs. Farmers like UDP because it saves them money and time because they only have to fertilize rice once instead of two or three times as with the broadcast approach and it causes fewer weeds to develop.

Although there has been a lot of interest in the factors that influence the adoption of this technology and its practices, as well as the spread of information and the impact of interventions that encourage them, there are still some knowledge gaps in the field. As a result, it's critical that this new information on UDP technology's potential adoption rate be leveraged to drive more usage. Improving access to this technology not only benefits smallholder farmers, but it can also benefit the rural poor because increased production leads to lower rice prices. Consequently, this research aimed at determining the potential adoption rate of UDP technology in the study area keeping in view the specific objectives viz. determinants of adoption level and intensity of technology use; adoption potential rate of the technology; and, the effect of adoption discrimination on yield.

2. MATERIAL AND METHODS

Kano state is in northern Nigeria, with latitudes ranging from 10° 33 to 12° 37N and longitudes ranging from 07° 34 to 09° 25E of the Greenwich meridian time. The northern and southern portions of the state's vegetation are characterized by Northern-Guinea savannah and Sudan savannah, respectively. The yearly rainfall in the Northern-Guinea savannah ranges from 600-1200 mm to 300-600 mm in the Sudan savannah. Furthermore, in the Sudan savannah region, arable crop growth seasons range from 90 to 150 days, and in the Northern-Guinea savannah region, they range from 150 to 200 days. The population of the state is predicted to reach 9.4 million people by 2050 (NPC, 2006), with a 3.5 percent annual growth rate.There are around 1,754,200 hectares of arable land in the state. The bulk of the state's people engaged in agricultural commodities trading, making it well-known for its commercial activity.

The sample size generated from multi-stage sampling technique for the study is composed of 300 rice farmers (192 adopters and 108 non-adopters). For the adopter, six out of the nine project located Local Government Areas (LGAs) were purposively selected given their comparative advantage in cultivation of rice. The selected LGAs were Bunkure, Garun-Mallam, Kura, Dambatta, Bagwai, and Makoda. This was followed by random selection of five participating localities from each of the selected LGAs. Thereafter, each of the chosen localities from LGAs-Bunkure, Garun-Mallam and Kura had selection of nine (9) respondents each while Dambatta, Bagwai, and Makoda had selection of four (4) respondents each, thus given a total sample size of 195 adopters. For the non-adopters- control group, given the absence of a definite sampling frame, a representative sample size of 108 respondents was generated by adopting the error margin formula proposed by Bartlett et al.(2001) (Equation 1). The distribution of the non-adopters was done in accordance with that of the adopter category. For the first three LGAs, from each of the selected five (5) localities, five non-adopters were randomly selected; while from the remaining three LGAs two (2) non-adopters were randomly selected from each of the chosen localities. Objectives I, II and III were achieved using Heckman's model, Treatment estimation model and Oaxaca-Blinder decomposition model respectively. A well structured questionnaire coupled with interview schedule was used to elicit information using easy-cost route approach owing to farmers' memory recall rather than book keeping which is absent among the respondents. It is worth to note that three questionnaires of the adopters had incomplete information, as such eliminated, thus living a total of 192.

$$n_n \equiv \frac{Z^2 * P(P-1)}{e^2} \qquad (1)$$

Where, n= finite sample size; Z = 1.645 (t-statistic at 10% level); P = 80% (proportion); and, e = error gap at 10% degree of freedom (0.10).

Heckman's Model: The model is made up of two parts: a choice model and an outcome model, with the former having a dichotomous dependent component and the latter having a continuous predict variable (Sadiq et al., 2021a).Because of its capacity to correct sample selection bias, the two-step Heckman's selection model was chosen. The model is shown below:

$$Y_i = f(X_1, X_2, X_3 \ldots \ldots X_n) \qquad (2)$$

$$Y_{it} = \beta_0 + \beta X_{it} + \varepsilon_i \qquad (3)$$

$Y_i^* = \alpha + X\beta + \varepsilon_i$ .... (4)

$Y_i^* = \alpha + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + X_4\beta_4 + X_5\beta_5 + \cdots . + X_n\beta_n + \gamma IMR + \varepsilon_i$ .... (5)

Equation 3 is a decision stage, a probit model with the dependent variable been binary while Equation 5 is an outcome stage, a censored model with the dependent variable been continuous.

Where, $Y_{it} = Adoption\ category(adopt = 1, otherwise = 0)$; Y_i* = latent observation of i[th] adopter (proportion (%) of farm size under UDP technology); X_1= Gender (male = 1, otherwise=0); X_2= Age (year); X_3= Marital status (married =1, otherwise=0); X_4= Educational level (year); X_5= Household size (number); X_6 = Rice farming experience/ farming experience (year); X_7 = Mixed cropping (yes= 1, otherwise=0); X_8 = Extension contact (yes=1, otherwise=0); X_9 = Seed variety (improved =1, otherwise=0); X_{10} = Duration of UDP adoption (year); X_{11} = Total farm size/ rice farm size (ha); X_{12}=Co-operative membership (yes=1, otherwise=0); X_{13} = Total livestock unit (TLU) (Camel=1.0; Horse=0.8; Cattle=0.7; Donkey=0.5; Sheep & Goat =0.1; and, Chicken=0.01); X_{14} = Market distance (km); X_{15} = Commercialization index (CI)(ratio of marketed surplus to marketable surplus); X_{16} = Dead stocks (capital assets);X_{17} = Yield (kg); IMR= The inverse Mill's ratio;β_0 = Intercept;β_{1-17} = Regression coefficient; γ= Lambda; and, ε_t = Stochastic.

Average Treatment Effect (ATE)

The average result difference between units assigned to care and units assigned to placebo is depicted in this graph (control). The following equation is based on Sadiq *et al.*(2021b):

Awareness index is given by: $E(y_{1i}|I = 1; X)$ … … … … … …. (6)

Non-Awareness index is given by: $E(y_{2i}|I = 0; X)$ … … …. (7)

Index of the awareness if there is no difference is denoted by: $E(y_{2i}|I = 1; X)$ … … … … … … … … … … … … … … … … … … … (8)

Index of non-awareness if there is difference is denoted by:$E(y_{1i}|I = 0; X)$ … … … … … … … … … … … … … … …. … … (9)

Where:
$E(.)$ = Expectation operator
y_{1i} = UDP Adoption (dependent variable)
y_{2i} = Non-Adoption (dependent variable)
I = Dummy variable (1 = awareness, 0 = non-awareness
X = Explanatory variables that is common to both.

$$\text{ATT} = E(y_{1i}|I = 1; X) - E(y_{2i}|I = 1; X) \ldots \ldots \ldots \ldots \ldots \ldots (10)$$

$$ATU = E(y_{1i}|I = 1; X) - E(y_{2i}|I = 1; X) \ldots \ldots \ldots \ldots \ldots \ldots \ldots (11)$$

Average Treatment Effect on Treated = ATET

Average Treatment effect on Untreated = ATEU

Equations (10) and (11) were further simplified as:

$$\text{ATT} = \frac{1}{N_1}\sum_{i=1}^{N_1}[p\,(y_{1i}|I = 1; X) - p(y_{2i} \mid I = 1; X)] \ldots \ldots \ldots (12)$$

$$\text{ATU} = \frac{1}{N_2}\sum_{i=1}^{N^2}[\,p\,(y_{2i}|I = 0; X) - p(y_{1i} \mid I = 0; X)] \ldots \ldots (13)$$

Where, $N_1$and N_2 are number of aware and non-aware farmers respectively, and p= probability.

Oaxaca-Blinder Decomposition Model

The following is the yield index function (Oaxaca 1973; Blinder 1973; Sadiq *et al*., 2020):

$$\bar{Y}_A = \beta_0 + \beta_i\sum_{i=1}^{i}X_i + \varepsilon_i \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (14)$$

$$\bar{Y}_{NA} = \beta_0 + \beta_i\sum_{i=1}^{i}X_i + \varepsilon_i \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (15)$$

Where, $\bar{Y}_A$= average yield of adopters; $\bar{Y}_{NA}$= average yield of non-adopters; $X_{i-n} = explanatory\ variables$; $\beta_0 = intercept$; $\beta_{i-n} = parameter\ estimates$; and, $\varepsilon_i = stochastic\ term.$

The total difference can be explain by,

$$\Delta Y = \bar{Y}_A - \bar{Y}_{NA} \ldots (16)$$

The Oaxaca-Blinder decomposition equation is,

$$\Delta Y = (\bar{X}_A\hat{\beta}_A - \bar{X}_{NA}\hat{\beta}_{NA}) + (\bar{X}_{NA}\hat{\beta}_A - \bar{X}_A\hat{\beta}_{NA}) \ldots (17)$$

If there is only discrimination against the non-adopters the formula becomes:

$$\Delta Y = (\bar{X}_A - \bar{X}_{NA})\hat{\beta}_A + (\hat{\beta}_A - \hat{\beta}_{NA})\bar{X}_{NA} + (\bar{X}_A - \bar{X}_{NA})(\hat{\beta}_A - \hat{\beta}_{NA}) \ldots (18)$$

If the non-adopter group has adopter group's coefficient, then the formula becomes:

$$\Delta Y = (\bar{X}_A - \bar{X}_{NA})\hat{\beta}_{NA} + (\hat{\beta}_A - \hat{\beta}_{NA})\bar{X}_{NA} + (\bar{X}_A - \bar{X}_{NA})(\hat{\beta}_A - \hat{\beta}_{NA}) \ldots (19)$$

Thus, Equations (18) & (19) have a 'threefold' decomposition, i.e. the outcome difference is divided into three components. The first, second and third components respectively, are endowment effect, discrimination effect and interaction effect.

The idea that there is a non-discriminatory coefficient vector that should be utilized to determine the contribution of the variations in the predictors leads to an alternative decomposition that is popular in the discrimination research. Let β^* be a non-discriminatory coefficient vector of this type. Following Jan (2008), the outcome difference can then be written as:

$$\Delta Y = (\bar{X}_A - \bar{X}_{NA})\beta^* + \{(\bar{X}_A)(\hat{\beta}_A - \beta^*) + (\bar{X}_{NA})(\beta^* - \hat{\beta}_{NA})\} \quad \ldots\ldots (20)$$

Therefore, Equation (20) has a 'twofold' decomposition, i.e. the outcome difference is divided into two components. The first and second are quantity effect and unexplained effect respectively. The latter is frequently attributed to discrimination, but it's vital to remember that it also includes all of the possible effects of unobserved variables.

3. RESULTS AND DISCUSSION

Determinants of UDP's adoption level and use intensity

The Wald Chi^2 being different from zero at 10% degree of freedom alongside the absence of interdependence-multicolinearity between the predictors as evident by their respective variance inflation factors (VIF) that are within the threshold value of 10.0 means that the chosen model is best fit for the specified equation (Table 1). Further, the non-plausibility of the Lambda's estimated coefficient viz. inverse Mill's ratio at 10% reinforced the validity, reliability and accuracy of the chosen model for future prediction as it implies that the model has no problem of sample selection bias in the use of non-zeros adoption intensity values.

A perusal of the results showed that improved seed varieties influenced both adoption level and intensity of UDP technology usage; gender, marital status, household size, extension contact and distance to market had influence on adoption status; while, rice farm size influenced adoption intensity as indicated by their respective parameter estimates that are within the acceptable margin of 10% error gap.

The positive-significant of improved seed varieties imply that UDP's adoption and intensity of use is high among the farmers that used improved seed varieties when compared to their counterparts that used non-improved (local) varieties. The possible reason may owes to the need to have potential yield level, which without the use of the technology- a precursor and catalyst, the major farm's goals will be in jeopardy. Therefore, the tendency of farmers that used improved seed varieties to adopt UDP over their counterparts (users of local varieties) will be 50.82% while the intensity of the technology usage will increase by 3.24% vis-à-vis 8.66 hectares. This high acreage increase is mostly likely among the medium to large-scale farmers if they observe economies of scale given their access to agricultural holdings.

The negative-significant of rice farm size implies that diseconomies of scale plummets the intensity of UDP adoption among the medium to large scale farmers. If the investment returns is not commiserate viz. increase in cost of cultivation vis-à-vis increase in yield, which in turns hampers the enterprise going concern due to mismatch in cost-benefit ratio, there is the tendency among the large-scale farmers to scale-down the intensity of UDP usage in the study area. Therefore, the marginal and elasticity implications of large-scale farmers scaling down their intensity in the use of UDP technology viz. cultivation size due to diseconomies of scale is likely to be 6.12 hectares and 7.65% respectively.

The negative-significant of gender coefficient indicates that poor access to productive resources among the women farmers affect them in the adoption of UDP technology. Gender stereotype due to religion and culture in the study area remains a challenge that hinders women's active participation in the downstream sector of agriculture, thus triggering their vulnerability to the vicious cycle of poverty. Therefore, the likelihood of women farmers not adopting this technology against their men counterparts is 67.26%. The coefficient of marital status being negatively signed and significant reveals that poor access to capital viz. social and economic capitals alongside less family responsibility to cater for affects the adoption of UDP technology among the farmers that are single. The social and economic capitals which are inherent in marriage are cogent veritable tools that will enable married farmers to be able to afford the resources to adopt the technology. In addition, the need to have an enlarged income so as to have access to better living standard for farm family will motivate married farmers to adopt the technology. Thus, the probability of non-married farmers not adopting the UDP technology in comparison to their counterparts (married farmers) is 73.93%.

The empirical evidence shows that large farm families are less likely to adopt the UDP technology as evident by the household size coefficient that is negatively signed and significant. The possible reason for poor adoption of the technology among this category of farmers may be attributed to population pressure that owes to the households being composed of vulnerable people- women and children: non-able bodied people, with little or no impact on external remittances. Thus, the probability of large household size opting out of UDP technology adoption will be 3.2% for any increase in household composition by one person as shown by the elasticity estimate of the respective variable.

The results showed that adoption of the technology was high among farmers that have access to extension services against their counterparts with no access as indicated by the extension estimated coefficient that is significant and positively signed. Proper guidance and support services from advisory services are impetus for attainment of potential farm objectives, thus strong motivational catalysts that encourages adoption of technologies especially among the mammoth/ large group of low educated farmers that characterized the farming settings in the study area. Therefore, the probability of farmers with extension access adopting the technology against their counterparts without is 108%. Closeness to the source of UDP technology encourages the adoption of the technology as indicated by the positive-significant of the estimated coefficient associated with distance to market. Proximity to markets where there exist perfect market competition *vis-à-vis* the input cost and readily available instructional information on the use of the technology among various sorts of agro-allied service dealers play a crucial role in motivating farmers at close distance to the market to adopt the technology. Therefore, the possibility of farmers with close proximity to markets to adopt the UDP technology is 16.20% against their counterparts whose proximity to the markets are far.

Table 1a. Determinants of adoption and use intensity

Items	Adoption status (decision)		Adoption intensity (outcome)		Elasticity
	Coefficient	t-stat	Coefficient	t-stat	
Intercept	−1.414(0.876)	1.613^{ns}	72.36(32.65)	2.216**	-
Gender	−0.672(0.306)	2.197**	-	-	-
Age	0.005(0.010)	0.537^{ns}	-	-	-
Marital status	−0.739(0.323)	2.285**	-	-	-
Education	0.011(0.018)	0.645^{ns}	0.247(0.325)	0.760^{ns}	0.0231
Household size	−0.032(0.017)	1.863*	-	-	-
Experience	0.019(0.013)	1.437^{ns}	-	-	-
Experience (rice)	-	-	0.209(0.232)	0.901^{ns}	0.0416
Mixed cropping	−0.503(0.308)	1.633^{ns}	-	-	-
Extension contact	1.083(0.371)	2.914***	−18.04(14.15)	1.274^{ns}	-0.2643
Seed variety	0.508(0.209)	2.429**	8.663(4.729)	1.832*	0.0324
DUDPA	-	-	0.292(0.903)	0.324^{ns}	0.0108
Farm size (total)	−0.020(0.065)	0.308^{ns}	-	-	-
Farm size (rice)	-	-	−6.123(3.467)	1.766*	-0.0765
CM	0.135(0.267)	0.504^{ns}	-	-	-
TLU	0.055(0.060)	0.919^{ns}	-	-	-
MD	0.162(0.047)	3.409***	-	-	-
CI	0.547(0.455)	1.201^{ns}	-	-	-
lnDS	0.099(0.072)	1.364^{ns}	-	-	-
Yield	-	-	0.803(3.314)	0.242^{ns}	0.0987
Lambda(IMR)	**-**	**-**	**1.009(9.767)**	**0.103^{ns}**	**-**
Sigma			**24.602**		
Rho			**0.0410**		
Wald Chi^2			**10.19[0.0177]****		

Source: Field survey, 2018

Note: *** ** * &^{ns} imply significant at 1%, 5%, 10% & non-significant, respectively.

DUDPA= Duration of UDP adoption; CM= Co-operative membership; MD=Market distance; lnDS= log of Dead stock.

Figures in ( ) and [ ] are standard error and probability level, respectively

Table 1b. Multicollinearity test

Variables	Variance inflation factors
Education	1.076
Experience (rice)	1.144
Extension contact	1.064
Seed variety	1.065
DUDPA	1.107
Farm size (rice)	1.288
Yield	1.168

UDP's Adoption Potentials

A perusal of the ATE results vis-à-vis all the estimation techniques shows that knowledge gained from participation in the Urea displacement project (UDP) had a positive-significant impact on the adoption rate of UDP technology in the studied area as evident by their respective ATE estimated coefficients which are positively signed and within the plausibility of 10% probability level (Table 2). The ATE coefficients of propensity score matching (PSM), regression adjustment (RA), nearest-neighbor matching (NNM), inverse probability weights (IPW) and IPW regression adjustment (IPWRA) being 0.1967, 0.2615, 0.2083, 0.2311 and 0.2287 respectively, implies that the awareness via USAID MARKETS II increase the adoption rate of UDP technology by 19.67, 26.15, 20.83, 23.11 and 22.87% respectively.

Furthermore, within the participating group, the empirical evidence establish that diffusion had positive impact on the adoption potential of the technology as indicated by all the respective estimation techniques of ATET coefficients which are positive signed and within the acceptable margin of 10% probability level. The ATET coefficients of the PSM, RA, NNM, IPW and IPWRA being 0.1587, 0.2306, 0.1958, 0.1941 and 0.1907 respectively, means that diffusion due to programme participation increase the potential adoption rate of the UDP technology among the adopters in the study area by 15.87, 23.06, 19.58, 19.41 and 19.07% respectively. However, on the other side, poor diffusion of the technology negatively affected the adoption potential rate of the technology among the non-participating group as indicated by the ATEU of all the respective estimation techniques which are negatively signed and different from zero at 10% probability level. The ATEU estimated coefficients of the PSM, RA, NNM, IPW and IPWRA being -0.2613, -0.3140, -0.2297, -0.2902 and -0.2779 respectively, implies that poor diffusion rate among the non-participating group plummeted the adoption potential of UDP technology by 26.13, 31.40, 22.97, 29.02 and 27.79% respectively. Therefore, it can be inferred that the programme knowledge awareness impacted significantly on the adoption and diffusion of the technology in the study area.

Further, based on the cursory review of the impact of the knowledge on the use of the UDP technology, the empirical evidences of the diffusion of the technology showed that only 63% of the farming population was aware of the technology (Table 2). This incomplete diffusion of the technology limits the adoption rate to 64% when the potential adoption rate is 98.44%, thus leads to an adoption gaps that hovers around 36.85 to 43.33%. Given the estimates of PSM, RA, NNM, IPW and IPWRA, the adoption gaps are 43.33, 36.85, 42.17, 39.89 and 40.13% respectively. Based on the selection bias vis-à-vis most of the estimation techniques, it can be inferred that all the farmers have an equal opportunity to adopt this technology. This demonstrates the consistency of the adoption of UDP technology among all the farmers in the studied area. Besides, it can be concluded that the UDP technology has a promising prospect in the studied area. In examining the UDP adoption rate across the estimated techniques, the PSM, RA, NNM, IPW and IPWRA showed 63% of the adopters with the possibility of gaining 19.67, 26.15, 20.83, 23.11 and 22.87% potential adoption rates respectively.

Table 2. Adoption potentials of UDP technology

Items	ATE			ATET			ATEU		
	Coeff.	SE	t-stat	Coeff.	SE	t-stat	Coeff.	SE	t-stat
PSM	0.196667	0.07755	2.54***	0.15873	0.066989	2.37**	-0.26126	0.146637	1.78*
RA	0.261483	0.061443	4.26***	0.230617	0.065277	3.53***	-0.31404	0.076917	4.08***
NNM	0.208333	0.07044	2.96***	0.195767	0.072242	2.71***	-0.22973	0.112062	2.05**
IPW	0.231141	0.059486	3.89***	0.19409	0.06225	3.12***	-0.29023	0.07743	3.75***
IPWR	0.228714	0.057883	3.95***	0.190698	0.059612	3.20***	-0.27785	0.067021	4.15***

Table 2. Continued

	Pop. (N)	Adopt (NA)	Exposed (NE)	A	B	AG	PBS	A%	B%	C
PSM	300	192	189	0.64	0.63	-0.43333	-0.03794	64	63	98.4375
RA	300	192	189	0.64	0.63	-0.36852	-0.03087	64	63	98.4375
NNM	300	192	189	0.64	0.63	-0.42167	-0.01257	64	63	98.4375
IPW	300	192	189	0.64	0.63	-0.39886	-0.03705	64	63	98.4375
IPWR	300	192	189	0.64	0.63	-0.40129	-0.03802	64	63	98.4375

Source: Field survey, 2018

Note: Pop. = Population; A = common adoption rate (NA/N); B= common adoption and expose rate (NE/N); A% = Adoption rate in the general population; B% = Rates of those who know; C= Rates of those who know and have adopted(NA/NE); AG = Adoption Gap (ATE-B); PBS = Population bias selection (ATE-ATET)

Discriminate effect of UDP technology on yield level

A cursory review of the results showed the average rice yield levels of the adopters and non-adopters to be 35.96 and 34.28 quintals respectively, leaving a gap of 1.69 quintals to be explained by the Blinder-Oaxaca Decomposition (Table 3). Of the gap, the threefold result showed discrimination effect termed structural difference due to adoption of the UDP accounted for 1.01 quintals; endowment effect due to differences in human factors accounted for -2.20 quintals while interaction effect holds on to 2.88 quintals. Thus, it can be inferred that interaction effect vis-à-vis combination of human factor-related and structural effects accounted for the major gap in the yield level between the adopters and non-adopters of UDP technology in the studied area. Furthermore, the results of Figure 1 showed most of the variables in the endowment component to have a statistically insignificant influence, except distance to market. It is obvious that the adopter versus non-adopter yield gap is driven by group differences in the proportion of individuals' distance to market. Thus, individuals with close proximity to market tend to gain more yield as evident from the pooled regression coefficient of distance to market. More so, the value of x.mean.diff indicated that a large proportion of the adopters of the technology are close to the market. Therefore, it can be inferred that the difference in the distance to market composition of the adopter and non-adopter groups accounted for some portion of the high yield achieved by the adopters of UDP technology. In the coefficient component, except rice farming experience, most of the variables are either insignificant or exhibits marginal significant influence. Thus, differences in the parameter estimates of rice farming experience account for decisive portion of the yield gap. Based on the rice farming experience coefficient differences between the two groups, it can be inferred that the yield gain for an additional year of rice farming experience is higher for the adopter group by 1.25%.

Table 3a. Summary of variables in the Oaxaca-Blinder decomposition model

Items	Beta A	Beta B	Beta Diff.	Reg. A	Reg. B	Reg. Pool 1	Reg. Pool2	Mean A	Mean B	Diff.
Intercept	39.22418	27.9987	11.22548	39.22	28	39.53	41.35	1	1	0
Gender	4.473236	13.61929	-9.14606	4.473	13.62	4.801	5.107	0.640625	0.814815	-0.17419
Age	-0.19379	-0.00483	-0.18896	-0.1938	-0.00483	-0.1805	-0.1826	39.96875	39.26852	0.700232
MS	0.121721	13.70013	-13.5784	0.1217	13.7	3.315	3.73	0.885417	0.907407	-0.02199
Education	-0.13209	0.63325	-0.76534	-0.1321	0.6332	0.1875	0.1772	5.989583	6.12037	-0.13079
EXR	0.464739	-0.78605	1.250789	0.4647	-0.7861	0.2142	0.2049	12.80208	12.5	0.302083
MC	-9.05241	-1.57052	-7.48189	-9.052	-1.571	-5.46	-5.288	0.854167	0.916667	-0.0625
Extension	3.710732	-0.98711	4.697844	3.711	-0.9871	0.8746	0.1512	0.979167	0.814815	0.164352
DM	1.081684	2.767762	-1.68608	1.082	2.768	1.708	1.593	2.828125	1.574074	1.254051
SV	1.401076	3.52578	-2.1247	1.401	3.526	0.7851	0.4435	0.322917	0.12963	0.193287
Farm size	-8.56346	-7.97406	-0.5894	-8.563	-7.974	-8.081	-8.224	0.803438	0.67213	0.131308
CM	-3.25564	-10.466	7.210352	-3.256	-10.47	-5.819	-5.975	0.869792	0.675926	0.193866
TLU	2.698875	-2.73447	5.433343	2.699	-2.734	0.9675	0.9441	1.238958	1.042315	0.196644
CI	2.831055	3.786765	-0.95571	2.831	3.787	3.23	2.904	0.713387	0.670659	0.042727
DS	1.51E-05	-9.1E-06	2.42E-05	1.51E-05	-9.1E-06	-9.7E-07	-7.6E-07	85522.03	102931.6	-17409.5
Class/mean							**-2.223**	35.96439	34.27876	1.685632

Source: Field survey, 2018

Note: Diff. = Difference; Reg. = Regression; MS = marital status; EXR = Experience (rice); MC = mixed cropping; DM = Distance to market; SV = Seed variety; CM = Co-operative membership; DS = Dead stock

Table 3b. Gap due to discrimination of adoption (Threefold decomposition)

Items	Endowment effect			Coefficient effect			Interaction effect		
	Coeff.	SE	t-stat	Coeff.	SE	t-stat	Coeff.	SE	t-stat
Intercept	0.000	0.000	0.000^{ns}	11.22548	20.69276	0.542^{ns}	0.000	0.000	0.000^{ns}
Gender	-2.372	1.298664	1.826*	-7.45234	7.485321	0.995^{ns}	1.59315	1.703522	0.935^{ns}
Age	-0.00338	0.427615	0.007^{ns}	-7.42028	2.393456	3.100***	-0.13232	0.61525	0.215^{ns}
MS	-0.30128	0.073839	4.080***	-12.3211	7.036827	1.750*	0.298599	0.124248	2.403***
Education	-0.08282	0.472753	0.175^{ns}	-4.68414	5.151241	0.909^{ns}	0.100096	0.576317	0.173^{ns}
EXR	-0.23745	0.597481	0.397^{ns}	15.63486	5.544397	2.819***	0.377843	0.122217	3.091***
MC	0.098157	0.623244	0.157^{ns}	-6.8584	3.628618	1.890*	0.467618	0.208279	2.245**
Extension	-0.16223	1.574623	0.103^{ns}	3.827873	7.914037	0.483^{ns}	0.772099	1.61536	0.477^{ns}
DM	3.470914	1.961137	1.769*	-2.65401	1.24442	2.132**	-2.11443	1.194978	1.769*
SV	0.681488	0.310328	2.196**	-0.27542	0.076215	3.613***	-0.41068	0.197192	2.082**
Farm size	-1.04706	0.371833	2.815***	-0.39615	3.600049	0.110^{ns}	-0.07739	1.056069	0.073^{ns}
CM	-2.029	1.124915	1.803*	4.873664	2.378449	2.049**	1.39784	1.802532	0.775^{ns}
TLU	-0.53772	0.165448	3.250***	5.663254	1.890864	2.995***	1.068432	1.557341	0.686^{ns}
CI	0.161798	0.079776	2.028**	-0.64096	10.59402	0.060^{ns}	-0.04083	0.406919	0.100^{ns}
DS	0.158054	0.992811	0.159^{ns}	2.486803	1.887656	1.317^{ns}	-0.42061	0.20577	2.044**
Effect	**-2.20287**	**0.566421**	**3.889*** **	**1.009082**	**0.395203**	**2.553*** **	**2.879417**	**1.443967**	**1.994** **
WD	**35.28784**			**35.28784**					
% of Disc.				**2.94**					

Source: Field survey, 2018

Note: Coeff. = Coefficient; SE = Standard error; WD = Without discrimination; Disc. = Discrimination

Table 3c. Gap due to discrimination of adoption (Twofold decomposition)

Items	Explained			Unexplained		
Weight	**Coeff.**	**SE**	**t-stat**	**Coeff.**	**SE**	**t-stat**
0	-2.20287	2.566421	0.858^{ns}	3.888499	2.723143	1.427^{ns}
1	0.67655	0.338812	1.996**	1.009082	3.095203	0.326^{ns}
0.5	-0.76316	0.316809	2.408**	2.44879	1.34477	1.820**
0.64	-0.36004	1.821734	0.197^{ns}	2.045672	2.51621	0.812^{ns}
-1	-0.06154	0.030757	2.001**	1.747168	1.024824	1.704*
-2	-0.53691	0.254261	2.111**	2.222546	1.264236	1.758*
WD(-1)	36.02593^			36.02593^^		
WD(-2)	36.5013^			36.5013^^		
% of Disc. (-1)				5.10		
% of Disc. (-2)				6.48		
	Unexplained A			**Unexplained B**		
	Coeff.	**SE**	**t-stat**	**Coeff.**	**SE**	**t-stat**
0	3.88849	2.72314	1.427^{ns}	0.000	0.000	0.000^{ns}
1	0.000	0.000	0.000^{ns}	1.009082	3.095203	0.326^{ns}
0.5	1.94424	1.16157	1.673^{ns}	0.504541	1.547601	0.326^{ns}
0.64	1.39986	1.74281	0.803^{ns}	0.645812	1.114273	0.579^{ns}
-1	0.628981	0.26533	2.370**	1.118188	0.362207	3.087***
-2	-3.1E-14	1.32E-14	2.331**	2.222546	0.764236	2.908***

Source: Field survey, 2018

Note: A = Adoption group; B = Non-Adoption group; WD = without discrimination; ^ = mean yield of Adopters minus endowment coefficient; ^^ = mean yield of non-adopters plus discrimination coefficient

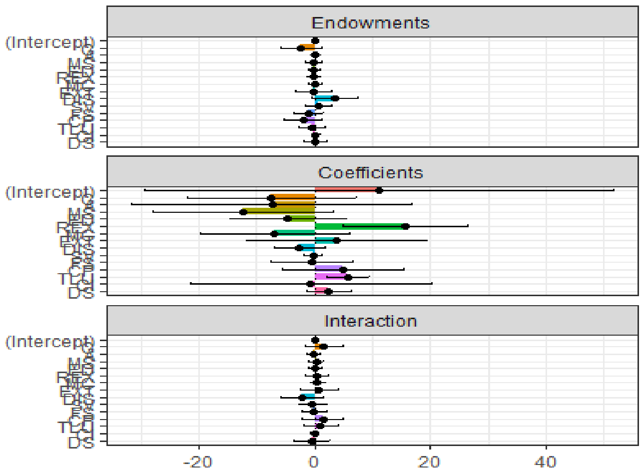

Figure 1. Threefold decomposition

Note: Age (A); Marital status (MS); Rice farming experience (REX); Mixed cropping (MC); Extension contact (EXT); Market distance (DIS); Rice farm size (FS); Co-operative membership (CP); Tropical livestock unit (TLU); Dead stock (DS)

The results of the twofold decomposition showed two negative weights that implies that the reference coefficients come from the pooled regression either without (-1) or with (-2) the group indicator variable included as a covariate (Table 3). The use of the pooled regression coefficients as a reference coefficient set excludes the group indicator variables of non-adopters. This is in line with previous works done by Hlavac (2018); Neumark (1988). In the weight column, the Neumark's decomposition is denoted by (-1). A perusal of the overall twofold decomposition results showed that the yield gap of 1.69 quintals between the adopters and non-adopters can be decomposed into -0.062 quintal that is explained by the group differences in the predictor variables and 1.747 quintals that is unexplained. While at weight (-2), the yield gap can be decomposed into -0.537 and 2.223 quintals respectively, which owes to explained and unexplained effects respectively. If it is assumed that the unexplained component of the yield gap happens due to technology discrimination, and the pooled regression coefficients are non-discriminatory, then the results at weights (-1) and (-2) revealed that 0.629 and -3.086E-14 quintals respectively, of the unexplained part originates from the discrimination in favour of the adopters (unexplained A) while 1.118 and 2.223 quintals in respect of the weight aforementioned emanates from discrimination against the non-adopters (unexplained B). The results of the variable-by-variable twofold decomposition depicted in Figure 2 are consistent with that of the threefold decomposition. Similarly, it was observed that the yield gap is govern by the higher proportion of individuals with close proximity to market among the adopters (explained component) and likewise their greater yield gain that owes to rice farming experience (unexplained component).

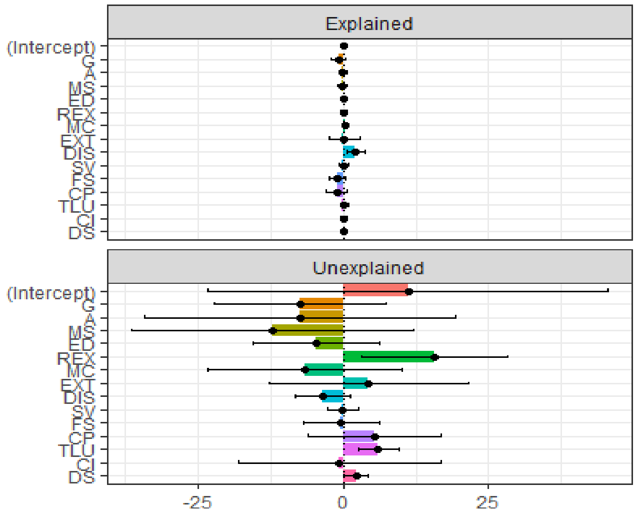

Figure 2. Twofold decomposition

Note: Gender (G); education (ED); Seed variety (SV); Commercialization index (CI)

In Figure 3, nine variables were used to visualize how much of the unexplained portion of the yield gap can be attributed to discrimination in favor of the adopters and how much owes to discrimination against the non-adopters. From the graph, it appears that only the discrimination component of rice farming experience achieved non-marginal statistical significance. From the bars, the relative size suggests that if it is assumed that the pooled regression coefficients reflect a non-discriminatory- almost thrice as much of the yield gap is explained by discrimination against the non-adopters compared to the discrimination in favor of the adopters. Besides, the side-by-side variable comparison is shown in Figure 4.

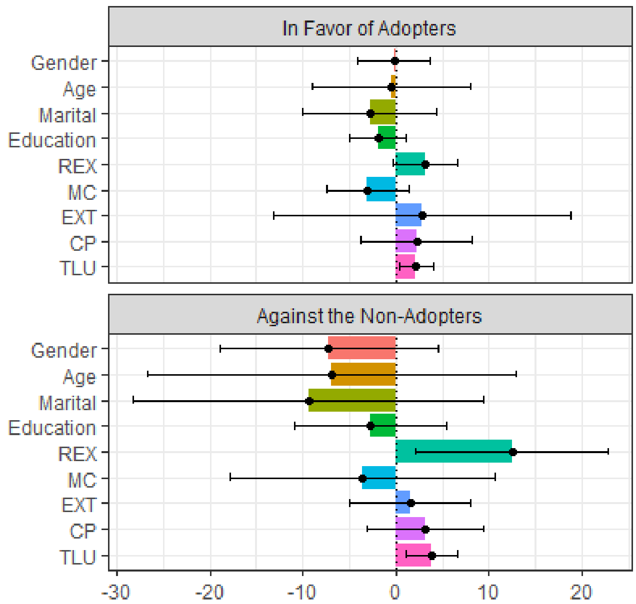

Figure 3. Variables vis-à-vis adopters and non-adopters

Further, at twofold decomposition, the empirical evidences showed that at weights (-1) and (-2), without discrimination against the non-adopters, their average yield level should be 36.03 and 36.50 quintals (approximately 36 quintals across) respectively.

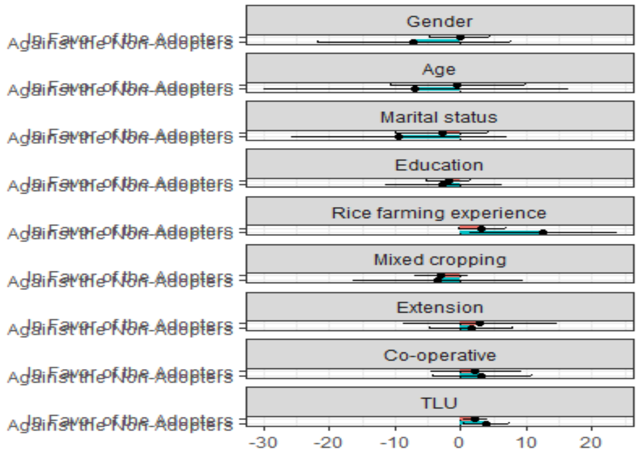

Figure 4. Side-by-side variable comparison

Note: Favor of adopters- first row; against non-adopters- second row

4. CONCLUSION

From the findings it was inferred that improved seed varieties has a dual influence on adoption and intensity of use of the UDP's technology. Further, it was found that the project has positive significant influence on the adoption rate of the technology. Besides, the potential rate of adoption was high but incomplete diffusion of the technology was found to be a barrier, thus created an adoption gap of 36.85-43.33%. More so, the empirical evidences showed that the composition of endowment-related factors and adoption discrimination effects- an interaction effect on one hand- threefold decomposition; and, adoption discrimination effect termed structural effect, a de facto on other hand- twofold decomposition played key roles in determining the yield gap between the adopters and non-adopters. Generally, it was concluded that the prospect of the technology in the studied area is very promising. Therefore, it was recommended that the project should scale-up the adoption rate of the technology preferably through farmer-to-farmer extension approach, an effective diffusion medium for a wider acceptability of the technology.

Compliance with Ethical Standards

Author Contributions

Authors contributed equally to this paper.

Conflict of Interest

The authors do not have any conflicts of interest to declare.

Ethical Approval

For this type of study, formal consent is not required.

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