African Journal of
Agricultural and Resource Economics
Volume 19, Number 3 (2024), pp 246–259

Adoption and yield impacts of improved groundnut varieties in Nigeria: Application of the potential outcomes framework

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Received: March 2024
Published: September 2024

DOI: https://doi.org/10.53936/afjare.2024.19(3).14

Abstract

Using the potential outcomes framework, we estimate the influence of the adoption gap, adoption drivers and impact of adopting improved groundnut varieties (IGVs) on groundnut yield among smallholder farmers in Nigeria. The results show a significant 34% adoption gap attributable to the lack of exposure of farmers to IGVs. With full exposure, the adoption rate could increase from the current 31% to about 65%. To close this adoption gap, policy options that empower agricultural extension staff to visit farmers more frequently, engage farmers in the development, testing and scaling activities of agricultural technology, and encourage farmers to join farmer groups are critical. Similarly, enabling households to access credit and input and output markets will lead to the increased probability of adopting IGVs. The study furthermore revealed a significantly positive impact of 148 kg/ha on the yield of IGVs, which represents a 20% average treatment effect on the treated (ATT) and a 22% average treatment effect on the untreated (ATU).

Key words: adoption gap, groundnut, impact assessment, Nigeria, productivity

1. Introduction

Sub-Saharan Africa (SSA) faces a myriad of development challenges, including high levels of poverty, and of food and nutrition insecurity. These problems are more pronounced in rural areas where the majority of the population resides, most of whom derive their livelihoods from smallholder agriculture that is characterised by a weak technological base and low productivity. This poor productivity has been attributed to the inadequate adoption of modern and well-adapted agricultural technologies like improved crop varieties (Tufa *et al*. 2019). Yet the famous "green revolution" in Asia has shown that the adoption of improved agricultural technologies can increase productivity and transform livelihoods (Pingali 2012). Even within SSA, studies have shown that the adoption of improved agricultural technologies, especially improved crop varieties, has positive and significant effect on increased productivity and reduced poverty, food and nutrition security (Tufa *et al*. 2019).

This challenge of low adoption of improved crop varieties in SSA has been studied extensively in Africa using different approaches (Pannell & Zilberman 2020). However, most of these past empirical studies estimated adoption without accounting for non-exposure and/or selection bias (Diagne & Demont 2007). Non-exposure bias stems from the fact that not all potential adopters in the population are usually exposed to the evaluated technologies. Therefore, using the sample adoption estimate will not be a true reflection of population adoption potential unless exposure to the technology was assigned randomly. Since exposure is seldom assigned randomly, this means that sample estimates suffer from selection bias. Therefore, the true adoption rate that reflects actual acceptance of the technology (adoption potential) should take care of this biasedness (exposure to improved varieties).

Using cross-sectional data collected from smallholder groundnut farmers in Nigeria, we estimated the actual and potential adoption rates of improved groundnut varieties (IGVs) and derived the adoption gap (difference between actual and potential adoption). We further estimated the impact of adopting IGVs on productivity. These results contribute to the limited but growing literature on the estimation of actual and potential adoption rates of agricultural technologies that have been conducted for other crops like rice (Nguezet *et al*. 2013), maize (Simtowe *et al*. 2019) and pigeonpea (Simtowe *et al*. 2011). To the best of our knowledge, no empirical study has estimated the groundnut adoption gap and the impact of adoption on groundnut productivity in Nigeria. However, knowing the technology adoption gap and adoption impacts on selected welfare outcomes like productivity is critical for investment decisions by donors, policy makers, researchers and farmers. The rest of the paper is organised as follows: Section 2 highlights the data and methods that have been used. The results and discussion are outlined in Section 3, while the summary and conclusions are in Section 4.

2. Data and methods

2.1 Data

This paper is based on household- and plot-level data collected from 1 470 smallholder rural groundnut farming households in five states of northern Nigeria (Bauchi, Jigawa, Kano, Katsina and Kebbi). A multi-stage sampling procedure was used to select the surveyed households. First, the five states were purposively sampled because they were sites for Tropical Legumes (TL) projects[1] and the USAID Groundnut Scaling project. In each state, three of the most important groundnut-producing local government authorities (LGAs) were purposively sampled, and three villages in each LGA were also purposively sampled based on the intensity of IGV scaling activities (demonstrations, field days, trials, seed production and upscaling). The three villages included two project intervention villages and one non-intervention village. From each village, 10 to 35 groundnut-farming households were randomly selected to make up 100 sampled households per LGA. Respondent farmers from the sampled households were interviewed by trained enumerators using semi-structured questionnaires that had been pre-tested. Data collected included household socioeconomic and demographic characteristics and groundnut production activities at the plot level, among other variables.

2.2 Empirical strategy

2.2.1 The average treatment effect (ATE) estimation of adoption

From the descriptive statistics (Table 1), only 55% of the sampled farmers were aware of IGVs and not all of them had adopted these varieties. We therefore estimated actual and potential adoption rates of IGVs using the potential outcomes framework proposed by Diagne and Demont (2007). In this approach, ATE is the average probability of adopting the target technology when the study unit (farm household) is randomly picked from the population, assuming that the whole population is exposed to the technology. Therefore, this approach measures the intrinsic value of the technology as perceived by the population. On the other hand, the observed sample adoption statistic is premised on a strong assumption that the whole population is exposed to the technology – an assumption that seldom holds in SSA, especially for agricultural technologies like improved crop varieties. The difference between the ATE adoption rate and the observed sample adoption rate (joint exposure and adoption rate) is the adoption gap due to technology exposure bias or incomplete technology diffusion bias (Diagne & Demont 2007). The adoption rate computed from the sub-sample that is aware of IGVs is what is referred to as the average treatment effect on the treated (ATT). The difference between the ATT and ATE is attributed to population selection bias (PSB). Similarly, the potential adoption rate computed from the sub-sample that is not aware of IGVs is called the treatment effect on the untreated (ATU).

Unlike the classical computation of population adoption from the sample, the ATE approach enables the estimation of consistent population adoption parameters conditional on a vector of observed covariates (x), such that

[1] TL II and TL III (later in the paper) refer to phases 2 and 3, respectively of a project funded by the Bill and Melinda Gades Foundation (BMGF) called Tropical Legumes (TL). The project is aimed at the development and dissemination of improved varieties of selected legume crops, including groundnut.

$$E(y_i|x), \tag{1}$$

where $E(y_i)$ is the expected adoption outcome or conditional ATE; and x is a vector of observed covariates. The identification of Equation (1) is based on the conditional independence assumption (CIA), which states that exposure to technology (w) is independent of adoption outcome (y_i), condictional on observed covariates of exposure (z). We therefore estimate ATE from a random sample of observed y_i, w_i, x_i and z_i (Equation (2)).

$$ATE = E(y_i|x) \;= E(y|x, w = 1) \tag{2}$$

The second equality of Equation (2), i.e. $g(x, \beta)$, is parametrically estimated based on the observed values of y_i and x_i from the sample that is exposed to improved technology only $(w = 1)$. After estimating the parameter $\hat{\beta}$ from $g(x, \beta)$, i.e. $g(x_i, \hat{\beta})$, the predicted values of the ATE from $g(x_i, \hat{\beta})$ are computed for the whole sample (exposed and non-exposed). Thereafter, ATE (Equation (3)), ATT (Equation (4)) and ATU (Equation (5)) are computed by obtaining the predicted values of the full sample, exposed sub-sample and non-exposed sub-sample, respectively.

$$\widehat{ATE} = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \hat{\beta}) \tag{3}$$

$$\widehat{ATT} = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta}) \tag{4}$$

$$\widehat{ATU} = \frac{1}{n_e}\sum_{i=1}^{n}(1 - w_i) g(x_i, \hat{\beta}) \tag{5}$$

From Equations (3), Equation (4) and Equation (5), the population adoption gap and the population selection bias can be estimated parametrically, as follows:

$$\widehat{PAG} = \widehat{JEA} - \widehat{ATE}, \text{ and} \tag{6}$$

$$\widehat{PSB} = \widehat{ATT} - \widehat{ATE}, \tag{7}$$

where $\widehat{JEA}$ in Equation (6) is the joint exposure and adoption parameter that is consistently estimated by the sample average of the observed adoption rate, given by Equation (8).

$$\widehat{JEA} = \frac{1}{n}\sum_{n=1}^{n} y_i \tag{8}$$

Beside estimating adoption using the ATE approach, the classic probit adoption model is also estimated, using the same explanatory variables and results compared across the two approaches. In the two models of exposure and adoption, variables used in past agricultural technology adoption studies were controlled for.

2.2.2 The local average treatment effect (LATE) estimation of impact

Following the potential outcome framework developed by Rubin (1974) and adopted by Nguezet *et al*. (2011), each study unit has two likely outcomes, Y_d, where the subscript d denotes adoption status (d =1 if an adopter and d = 0 if a non-adopter). The study unit could be a household, a plot, etc. In this paper, the study unit was a groundnut plot that could have been planted with an improved groundnut variety (adopter) or a local groundnut variety (non-adopter). On the other hand, potential outcome could be any welfare outcome, such as poverty, income, food security, etc. In the current study, potential outcome (impacted variable) was groundnut productivity (yield). Therefore, the impacted variable could be represented as a function of two potential outcomes:

$$Y = dY_1 + (1 - d)Y_0 \tag{9}$$

The implication of Equation (9) above is that the impact of the treatment (d) on the outcome (Y) is the difference between the observed outcome (Y_d) under $d = 1$ and $d = 0$, i.e. $Y_1 - Y_0$. However, since Y_1 and Y_0 cannot be observed at the same time *ex post* (the two outcomes are mutually exclusive), several approaches have been developed to model the average impact of the treatment on the outcome among the treated and the untreated units. In impact assessment literature, the actual impact of the treatment on the treated units, $E(Y_1 - Y_0/d = 1)$, is called the average treatment effect on the treated (ATT), while the potential impact of the treatment on the untreated, $E(Y_1 - Y_0/d = 0)$, is referred to as average treatment effect on the untreated (ATU). Overall, the estimated population average treatment effect (ATE) is the summation of ATT and ATU at their means. The challenge in the literature has been to disentangle the effect of the treatment on the outcome variable. Innovative approaches have been proposed and applied in the empirical literature to isolate the part of the outcome variable that is attributable to the treatment by controlling for treatment biases due to observed and/or unobservable characteristics (Lee 2006). Therefore, to control for observed bias, we first computed ATT (Equation 10), ATU (Equation 11) and ATE (Equation 12) using the inverse propensity score weighting (IPSW) estimator that is based on the conditional independence assumption. In this IPSW estimation approach, the ATT, ATU and ATE were computed following Imbens (2004), and as adopted by Nguezet *et al*. (2011) and Awotide *et al*. (2013), as follows:

$$A\hat{T}T = \frac{1}{n_1}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{(1-\hat{p}(x_i))}, \tag{10}$$

$$A\hat{T}U = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)}, \text{ and} \tag{11}$$

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)(1-\hat{p}(x_i))}, \tag{12}$$

where n is the sample size; $n_1 = \sum_{n=1}^{n} d_i$ is the number of the treated (adopters of IGVs); and $\hat{p}(x_i)$ is the adoption propensity score estimated using a probit model with x covariates. Secondly, to control for unobserved bias, we adopted the instrumental variable (IV) approach to estimate the impact of adopting improved groundnut varieties on yield in a local average treatment effect (LATE) framework (Imbens & Angrist 1994).

LATE is the average effect of the treatment on adopters who adopted after exposure to the treatment, and potential adopters who did not adopt due to a lack of exposure to the treatment. In this IV approach, two LATE estimators can be generated based on assumptions about the treatment instrument, i.e. exposure to IGVs (w). First, when the instrument is assumed to be random, we use the Wald estimator (Imbens & Angrist 1994). The Wald estimator is non-parametric and needs only the outcome variable (Y), the treatment variable (d) and the instrument (w) to be computed:

$$LATE = E(Y_{1i} - Y_{0i}|d_1 = 1) = \frac{E(Y|w=1) - E(Y|w=0)}{E(d|w=1) - E(d|w=0)} \tag{13}$$

From Equation (13), the LATE parameter can consistently estimate the Wald estimator, as follows:

$$\widehat{LATE} = \left[\frac{\sum_{i=1}^{n} Y_i w_i}{\sum_{i=1}^{n} w_i} - \frac{\sum_{i=1}^{n} Y_i (1-w_i)}{\sum_{i=1}^{n} (1-w_i)}\right] \times \left[\frac{\sum_{i=1}^{n} d_i w_i}{\sum_{i=1}^{n} w_i} - \frac{\sum_{i=1}^{n} d_i (1-w_i)}{\sum_{i=1}^{n} (1-w_i)}\right]^{-1} \quad (14)$$

Second, since in most non-experimental observational data cases the instrument is not random – like the current study, where awareness of IGVs is unlikely to be random – we generate LATE using the local average response function (LARF) estimator. The LARF estimator is a Wald estimator, but generalised by Abadie (2003) to cases where the instrument becomes random only after controlling for x covariates that determine the observed outcome Y (Diagne 2012; Nguezet *et al*. 2011). Therefore, we estimated LATE using the more generalised LARF estimator, as follows:

$$\widehat{LATE_{LARF}} = \frac{1}{\hat{P}(d_1 = 1)} \sum_{i=1}^{n} \widehat{k_i} \bullet h(Y_i, x_i, \widehat{\theta}) \quad (15)$$

Following Nguezet *et al*. (2011), the natural candidate for the treatment instrument in this study was a binary variable (w) describing whether the household that operated the groundnut plot was aware of any IGV or not ($w = 1$ if aware; $w = 0$ if otherwise). This is a natural instrument because awareness is a necessary condition for adoption, and awareness of IGVs can only affect groundnut yield through the adoption of those improved varieties.

3. Results and discussion

3.1 Adoption of improved groundnut varieties (IGVs)

3.1.1 Descriptive results of adoption

The sampled households were found to have been aware of about 14 different groundnut varieties, of which eight were improved (Table 1). Among the IGVs, SAMNUT24 was the most widely known (38%) and widely adopted (25%). Overall, about 55% of the sampled households were aware of at least one IGV, and about 31% had adopted at least one of the IGVs (Table 1). Therefore, not all households that were aware of IGVs had adopted them. The 31% adoption rate was based on the whole sample and is likely to be an underestimation or overestimation of adoption potential, unless the whole population from which the sample was drawn had been exposed to IGVs or exposure was randomly assigned. But it is already clear that not all households were exposed to IGVs, and neither was exposure randomly assigned. Households in the sampled villages selected themselves into the group that was aware and not aware of IGVs based on their observed and unobserved characteristics. Therefore, there is a need to control for exposure.

Following this exposure argument, the descriptive statistics of adoption by the sub-sample that had been exposed to IGVs showed an adoption rate of about 56% (Table 1). This means that there is an adoption gap of about 25% due to a lack of exposure/awareness. Since no causal inference can be drawn based on these descriptive statistics, there is a compelling need to parametrically analyse the factors limiting exposure to IGVs and eventual adoption.

Table 1: Awareness and adoption of improved groundnut varieties

Groundnut variety	Variety category	Year of release	Aware (%) (N = 1 470)	Unconditional adoption (N = 1 470)	Adoption among exposed (N = 809)
SAMNUT 10	Improved	1988	3.5	0.5	1.0
SAMNUT 11	Improved	1988	1.5	0.2	0.4
SAMNUT 21	Improved	2001	4.6	2.2	4.0
SAMNUT 22	Improved	2001	2.4	0.2	0.4
SAMNUT 23	Improved	2001	5.4	1.4	2.6
SAMNUT 24	Improved	2011	37.8	24.6	44.6
SAMNUT 25	Improved	2013	10.2	0.8	1.5
SAMNUT 26	Improved	2013	9.5	2.4	4.4
Maiborgo	Local	n/a	29.7	7.1	n/a
Yardakar	Local	n/a	35.0	7.4	n/a
Kampala	Local	n/a	7.1	2.3	n/a
Manipinta	Local	n/a	0.1	0.0	n/a
Kwankwaso	Local	n/a	27.0	15.4	n/a
Burguwa	Local	n/a	4.4	3.0	n/a
Improved varieties	Improved	n/a	55.0	30.5	55.5

Further descriptive statistics showed that about 35% of non-adopters were already aware of IGVs (Table 2). About 65% of the sampled households were from villages involved in the TL III/USAID Groundnut Scaling Project, and a significantly higher proportion of adopters (86%) compared to non-adopters (56%) were from these villages. This higher proportion of adopters coming from TL III/USAID Groundnut Scaling Project villages could be attributed to the robust promotional activities that were undertaken by the two projects to create awareness of and improve access by the households in these villages to seeds of the promoted IGVs. This assertion is consistent with the descriptive results, showing that a significantly higher proportion of adopting households had been engaged in groundnut technology-upscaling activities (trials, demonstrations, field days) compared to non-adopting households. While about 21% of the sampled households were engaged in IGV technology-scaling activities, about 32% and 16% of adopters and non-adopters, respectively were involved in these technology-scaling activities (Table 2).

Table 2: Descriptive statistics for household-level variables

Variable	Pooled (N = 1 470)	Adopter (N = 449)	Non-adopter (N = 1 021)	Mean difference
Aware of improved groundnut varieties (1 = Yes; 0 = No)	0.55 (0.50)	1.00 (0.00)	0.35 (0.48)	0.65***
TL III Project village (1 = Yes; 0 = No)	0.65 (0.48)	0.86 (0.35)	0.56 (0.50)	0.30***
Household head age (years)	45.34 (11.96)	45.47 (11.19)	45.29 (12.28)	0.18
Household head sex (1 = Male; 0 = Female)	0.92 (0.27)	0.91 (0.29)	0.93 (0.26)	-0.02
Household head marital status (1 = Married; 0 = Otherwise)	0.96 (0.20)	0.96 (0.20)	0.96 (0.19)	-0.00
Household head main occupation (1 = Farming; 0 = Otherwise)	0.85 (0.36)	0.86 (0.35)	0.84 (0.36)	0.02
Household head education (years)	3.35 (6.86)	3.00 (6.18)	3.50 (7.14)	-0.50
Household size (number of members)	9.60 (7.65)	9.84 (9.16)	9.50 (6.88)	0.35
Household membership of a farmer group (1 = Yes; 0 = No)	0.33 (0.47)	0.41 (0.49)	0.29 (0.45)	0.12***
Household visited by agricultural extension agent (1 = Yes; 0 = No)	0.60 (0.49)	0.77 (0.42)	0.53 (0.50)	0.25***

Variable	Pooled (N = 1 470)	Adopter (N = 449)	Non-adopter (N = 1 021)	Mean difference
Household accessed credit (1 = Yes; 0 = No)	0.09 (0.29)	0.13 (0.34)	0.08 (0.26)	0.06***
Household engaged in technology-upscaling activities (1 = Yes; 0 = No)	0.21 (0.41)	0.32 (0.47)	0.16 (0.37)	0.16***
Household had problems in accessing input/ output markets (1 = Yes; 0 = No)	0.19 (0.39)	0.17 (0.38)	0.19 (0.39)	-0.02
Bauchi State (1 = Yes; 0 = No)	0.21 (0.40)	0.18 (0.38)	0.22 (0.41)	-0.04*
Jigawa State (1 = Yes; 0 = No)	0.20 (0.40)	0.31 (0.47)	0.15 (0.36)	0.16***
Kano State (1 = Yes; 0 = No)	0.20 (0.40)	0.11 (0.31)	0.25 (0.43)	-0.14***
Katsina State (1 = Yes; 0 = No)	0.20 (0.40)	0.27 (0.45)	0.17 (0.38)	0.10***
Kebbi State (1 = Yes; 0 = No)	0.19 (0.39)	0.13 (0.34)	0.21 (0.41)	-0.08***

Notes: *** = p < 0.01, ** = p < 0.05, * = p < 0.1; values in parenthesis are standard deviations

Also, there was a significant difference between adopting and non-adopting households in the proportion of households that were visited by an agricultural extension agent and had membership of farmer groups. While about 60% of the sampled households had been visited by agricultural extension officers, a significantly higher proportion of adopting households (77%) were visited compared to non-adopting households (53%). These findings emphasise the importance of exposure to technologies in influencing adoption. Visits by agricultural extension agents and involvement in agricultural technology testing and scaling activities, like trials, demonstrations and field days, give households an opportunity to be exposed to improved agricultural technologies. Further, a significantly higher proportion of households adopting improved varieties were members of farmer groups compared to non-adopters (Table 2). Farmer groups are social capital institutions, and they are likely to enhance the exchange of information and social learning about new technologies (Uaeieni 2011). Lastly, a significantly higher proportion of households that had adopted improved groundnut varieties had accessed credit (13%) compared to those who had not adopted (8%). This statistic emphasises the importance of credit in enabling households to adopt improved agricultural technologies and is consistent with past empirical findings (Hu *et al*. 2019).

3.1.2 Determinants of exposure to and adoption of improved groundnut varieties

About 55% of the sampled households were exposed to at least one of the eight IGVs (Table 1). The unconditional sample adoption rate was about 31%. The results show that some variables were significant in determining exposure to IGVs, but insignificant in influencing adoption and vice versa. Similarly, there were variables that significantly determined both exposure and adoption. The age of the household head was found to significantly affect the exposure of households to IGVs, but not adoption (Table 3). Households headed by older people were more likely to be exposed to improved varieties compared to those headed by younger people. This finding could be attributed to the possibility that older household heads – compared to younger household heads – have more experience in farming and also have wider social networks from which they can easily get information about new varieties compared. In fact, we found that membership of farmer groups had a positive and highly significant effect on the probability of household exposure to IGVs. Interestingly, while we found a significant effect of membership of farmer groups on exposure to IGVs and an insignificant effect on adoption (Table 3), Wossen *et al*. (2017) find a positive and significant effect of membership of farmer groups on the adoption of improved agricultural technologies. However, unlike in the current study, where we used the ATE framework to assess adoption, Wossen et *al*. (2017) used the classical probit model that is likely to generate inconsistent and biased estimates, as outlined in the methodology section above. In fact, we also obtained similar results to those of Wossen *et al*. (2017) when we used the classical probit model to assess adoption (Table 3). The positive and significant effect of membership of farmer groups on exposure to IGVs is a clear demonstration of the importance of social networks in enabling farmers to have access information about improved agricultural technologies. Social learning achieved through social networks/capital has been demonstrated empirically to be critical for enhancing access to agricultural productivity-enhancing technologies (Simtowe *et al*. 2019; Norton & Alwang 2020).

Table 3: Determinants of exposure to and adoption of improved groundnut varieties

Variable label	Model 1: Exposure	Model 2: Adoption among exposed	Model 3: Classical probit model
Household head age (years)	0.01** (0.00)	-0.00 (0.00)	0.00 (0.00)
Household head sex (1 = Male; 0 = Female)	0.13 (0.14)	0.03 (0.18)	0.07 (0.14)
Household head marital status (1 = Married; 0 = Otherwise)	-0.42** (0.20)	0.06 (0.25)	-0.06 (0.20)
Household head main occupation (1 = Farming; 0 = Otherwise)	-0.27** (0.11)	0.32** (0.13)	0.12 (0.11)
Household head education (years)	-0.02** (0.01)	0.00 (0.01)	-0.00 (0.01)
TL III Project village (1 = Yes; 0 = No)	0.57*** (0.08)	0.47*** (0.12)	0.68*** (0.10)
Household visited by agricultural extension agent (1 = Yes; 0 = No)	0.26*** (0.08)	0.52*** (0.12)	0.47*** (0.09)
Household size (number of members)	-0.01* (0.01)	-0.01 (0.01)	-0.02** (0.01)
Household engaged in technology-upscaling activities (1 = Yes; 0 = No)	0.24** (0.10)	0.36*** (0.12)	0.39*** (0.10)
Household membership of a farmer group (1 = Yes; 0 = No)	0.34*** (0.08)	-0.01 (0.11)	0.16* (0.09)
Household accessed credit (1 = Yes; 0 = No)	0.08 (0.13)	0.49*** (0.18)	0.36*** (0.12)
Household had problems in accessing input/ output markets (1 = Yes; 0 = No)	-0.21** (0.10)	-0.30** (0.13)	-0.27** (0.11)
State	Yes	Yes	Yes
Constant	-0.05 (0.24)	-0.48* (0.29)	-1.23*** (0.25)
Number of observations	1 470	809	1 470
Wald $chi^2(16)$	307.85	104.47	256.15
Prob > chi^2	0.00	0.00	0.00
Pseudo R^2	0.15	0.10	0.16
Log pseudolikelihood	-857.54	-498.27	-759.84

Notes: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$; values in parenthesis are standard errors

Other variables that significantly affected exposure but not the probability of adopting IGVs were marital status and education of the household head, together with household size. These variables were negatively and significantly related to the probability of exposure to IGVs (Table 3). Households with heads who were not married had a higher probability of being exposed to IGVs, probably because most research and development projects in SSA normally target vulnerable households like those headed by widows, widowers, divorced and single parents. On the other hand, the negative and significant effect of education on probability of exposure to IGVs could be explained by the possibility that more educated household heads derive their livelihoods outside agriculture, and therefore they are less motivated to find out about new agricultural technologies compared to less educated household heads, who are mainly dependent on agriculture. Similarly, large household size reduced the probability of exposure to IGVs (Table 3). This latter finding could be driven by the possibility that large household sizes are synonymous with a high dependence ratio, thereby limiting the ability for interaction with other farmers, such as in farmer groups, where information about improved varieties could be shared (Sheahan & Barrett 2014).

As expected, households in project villages had a higher and more significant probability of exposure to and adoption of IGVs than others (Table 3). Therefore, interventions by research and development projects to promote and popularise modern technologies are critical for raising awareness and increasing the probability of adoption. Similarly, visits to households by agricultural extension staff and involving households in technology-upscaling activities (trials, demonstrations, field days, etc.) increases the likelihood of exposure to and adoption of IGVs (Table 3). These visits by extension staff and participation in technology-scaling activities tend to provide more information about new technologies, thereby reducing ambiguity and perceived risks. Therefore, empowering extension agents to visit/contact farmers and involving households in agricultural technology-scaling activities will not only expose these households to improved technologies like IGVs, but will also increase their probability of adoption. These findings are consistent with Wossen *et al*. (2017) in Nigeria and Norton and Alwang (2020) in their literature review of overall adoption.

Although not important for determining exposure to IGVs, access to credit was positively and significantly associated with the adoption of IGVs (Table 3). Access to credit has been found to be a wealth and risk-mitigation indicator in previous literature. Those who access credit are considered relatively better off (wealthier) than those who do not, and access to credit has been shown to mitigate the risk aversiveness of rural farming households. On the other hand, those households that had constraints in accessing input and/or output markets were unlikely to be exposed to IGVs, and similarly were unlikely to adopt them (Table 3). Poor market access reduces the likelihood of accessing information about improved agricultural technologies and dampens adoption probability (Mujeyi *et al*. 2019). Remoteness (poor access to markets) is associated with higher transaction costs of accessing information and physical technologies, and thus poses less of a likelihood of adoption.

The unexpected finding was the effect of the main occupation of the household head on the probability of exposure to IGVs. The results showed that households headed by individuals whose main occupation was farming were unlikely to be exposed to IGVs compared to others (Table 3). The expectation was that, if the main occupation of the household head was farming, there was a motivation to find out about new farming technologies that could boost household income. However, this unexpected finding could be driven by the possibility that full-time farmers spend most of their time on the farm, thus missing out on interacting with other people who could share information and expose them to new technologies (Awotide *et al*. 2013). However, once exposed to IGVs, household heads whose main occupation is farming are more likely to adopt than others. Therefore, technology awareness and promotional activities targeted at household heads whose main occupation is farming are critical for increased adoption and the eventual desired genetic gains from agricultural research.

3.1.3 Actual and potential adoption rates of improved groundnut varieties

The descriptive statistics and ATE results consistently showed a statistically significant joint exposure and adoption rate (JEA) of the sample of about 31% (Table 1 and Table 4). However, as already mentioned, this 31% does not reflect the true adoption potential, unless the whole population is either exposed to IGVs or exposure is assigned randomly to the target population. Consequently, a parametric estimation of IGV adoption among sampled households that had been exposed to IGVs (ATT) showed an adoption rate of about 67%. However, this 67% adoption rate could still be inconsistent, because the same propensity to adopt cannot be assumed to exist among the sub-sample that was not exposed to IGVs. Therefore, estimating the probability of adopting IGVs among those households that were not exposed to them (ATU) showed an adoption rate of about 63% (Table 4).

On the other hand, the estimated ATE for the population adoption rate conditional on full exposure was about 65%. This is the probability of adopting IGVs in northern Nigeria if all groundnut-farming households were exposed to IGVs. Comparing the observed sample adoption rate of 31% (JEA row in Table 4) and the potential population adoption rate of 65% (ATE row in Table 4) therefore showed that there is a significant adoption gap of about 34% (GAP row in Table 4). This finding indicates that there is potential to significantly increase the adoption of IGVs if the whole population would be exposed to them. Similar findings of a significant adoption gap due to incomplete exposure have been documented in Tanzania for pigeonpea (Simtowe *et al*. 2011) and rice in Nigeria (Diagne 2010). The need for increased activities to create awareness of technology among smallholder groundnut farmers in northern Nigeria is backed up by the fact that the population selection bias (PSB) parameter from the parametric analysis was positive and significant (PSB row in Table 4). This implies that households that were exposed to IGVs have a higher probability of adoption than those that had not been exposed. Therefore, as noted by Diagne (2010), the low adoption of improved agricultural technologies in SSA is significantly due to a lack of awareness.

Table 4: Parametric estimates of average treatment effect (ATE) of population adoption rates

Estimator	Parameter
ATE	0.65*** (0.02)
ATT	0.67*** (0.02)
ATU	0.63*** (0.03)
JEA	0.31*** (0.01)
GAP	-0.34*** (0.02)
PSB	0.03** (0.01)

Notes: *** = $p < 0.01$, ** = $p < 0.05$; values in parenthesis are standard errors

3.2 Impact assessment of improved groundnut varieties (IGVs) on groundnut productivity

While the assessment of the adoption of IGVs was conducted at the household level, the impact assessment of IGVs on yield was analysed using plot-level data. The sampled households were found to be cultivating about 1 654 groundnut plots, and the observed average yield for IGVs was about 741 kg/ha compared to 679 kg/ha for local groundnut varieties (LGVs). This yield difference (62 kg/ha) was statistically significant (Table 5). In addition to these results, which are based on a simple *t*-test, the impact of IGVs on yield was estimated using two ATE estimators, i.e. the non-parametric ATE inverse propensity score weighting (IPSW) and the parametric ATE with interaction terms (Table 5). On the other hand, the LATE estimation results can be based on Wald or LARF estimators. In this study, we present and discuss results from the LARF estimator, because the Wald estimator of LATE relies on the strong assumption that the instrument should be completely random, while LARF relaxes this assumption.[2]

[2] The instrument used in this study, i.e. awareness of IGVs, is not random, since farmers self-selected themselves into the group that is aware of the IGVs and into the group that is not aware of IGVs, conditional on some observed and unobserved covariates.

The results from the non-parametric IPSW method show that ATE was about 182 kg/ha. This is the average yield advantage that any plot picked randomly from the population in which the sampled groundnut growers were drawn would have if it were to be planted with IGVs. However, the estimated average impact of IGVs in plots that were planted with IGVs (ATT) was about 155 kg/ha. The implication of this latter finding is that, had these plots with IGVs been planted with LGVs, then their yields could have been 155 kg/ha less than what was observed on these plots at the time of this study. Therefore, IGV adoption resulted in a 26% yield increase on plots with IGVs. Similarly, a significant ATE of IGVs was observed among LGVs plots (ATU). Had LGV plots been planted with IGVs, the yield could have been increased significantly, by about 201 kg/ha (Table 5), and this represents an ATU impact of about 30%. Similarly, parametric estimates showed a significant IGV impact on ATE, ATT and ATU (Table 5). The estimated ATE was 173 kg/ha, ATT was 132 kg/ha and ATU was 204 kg/ha, representing positive impacts of 25%, 18% and 30%, respectively. Since the impact of IGVs is more pronounced on plots that are currently under LGVs, this calls for concerted efforts to enable more groundnut plots to be planted with IGVs for increased production.

Table 5: Econometric estimation of the impact of improved groundnut varieties (IGVs) on productivity

Parameter	Parameter estimate	Robust std err	z
Observed difference	61.95**	27.64	2.24
Improved varieties	741.20***	20.63	35.92
Local varieties	679.24***	18.40	36.92
Non-parametric ATE estimator (IPSW)			
ATE	181.84***	36.97	4.92
ATT	154.69***	30.01	5.15
ATU	201.48***	49.37	4.08
PSB	-27.15	24.26	-1.12
Parametric ATE estimator (with interaction terms)			
ATE	173.43***	29.29	5.92
ATT	131.63***	30.43	4.33
ATU	203.66***	32.89	6.19
PSB	-41.79***	14.80	-2.82
LATE LARF estimator			
LATE	148.21***	0.00	9.30E+08

Note: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.01$

On the other hand, the LARF estimator of LATE showed that IGVs have a significantly positive impact on productivity (Table 5). IGVs were found to have a significant LATE, of about 148 kg/ha. This implies that any plot picked randomly among the groundnut-growing farmers could yield almost 148 kg/ha more if it was planted with IGVs compared to LGVs. Therefore, the ATT of the LARF estimator is about 20%, i.e. the yield of the IGV plot could have dropped from 741 kg/ha to about 593 kg/ha if the same plot was under LGVs. On the other hand, the ATU from the LARF estimator was about 22%, which means that the yield of the LGV plot could have increased from the observed 679 kg/ha to about 827 kg/ha. Therefore, these results demonstrate the importance of awareness of IGVs in determining adoption, along with the significant impact of IGV adoption, on boosting groundnut productivity in Nigeria. Whether this increased productivity stemming from the adoption of IGVs will lead to an improvement in key welfare outcomes, such as reduced poverty and improved food and nutrition security, is an area worth exploring in future research.

4. Conclusion and implications

Sub-Saharan Africa (SSA) has disproportionately high poverty, food and nutrition insecurity challenges compared to other regions of the world. These challenges are more pronounced among rural farming households, which continue to use archaic technologies like local crop varieties that are less productive. The reasons for this low adoption have been studied using different approaches that make generalisation of the results across different geographies within this region difficult. Therefore, using household- and plot-level data collected in northern Nigeria, we analysed the adoption and impact of improved groundnut varieties (IGVs) on productivity (yield). We applied the potential outcomes framework to estimate the adoption gap and analyse adoption drivers. Subsequently, the average treatment effect (ATE) and local average treatment effect (LATE) models were used to assess the impact of IGVs on groundnut yield. The results showed a significant adoption gap of 34% attributable to a lack of exposure to IGVs. With full exposure, the adoption rate would have the potential to increase from the current 31% to almost 65%. Furthermore, the results showed that addressing agricultural extension constraints, engaging farmers in technology development, testing and promotion, and encouraging farmers to join farmer groups are critical for exposing them to IGVs. Also, relaxing agricultural extension constraints and engaging households in technology development, testing and promotion will increase their exposure to and adoption of IGVs. Credit and market access are also critical in increasing the adoption of IGVs. This study furthermore found a positive and significant impact of IGVs on groundnut productivity.

Acknowledgements

We gratefully acknowledge the financial support for this research from the Bill and Melinda Gates Foundation (BMGF), Seattle, WA [grant number OPP1114827 and OPP1198373] and the United States Agency for International Development (USAID), Washington Bureau.

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