Adoption and impact assessment of improved groundnut varieties on poverty using DNA-Fingerprinting data: Evidence from smallholder rural farmers in Northern Nigeria

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Abstract

Poverty among rural farming households in sub-Saharan Africa (SSA) is associated with low adoption of modern farming technologies, especially improved crop varieties. Most studies that investigated adoption and impacts of improved crop varieties in SSA are based on farmers' self-reported adoption status and average treatment effects. However, farmers self-reported adoption status is susceptible to errors and assessing adoption impacts using average treatment effects do not account for farmers' heterogeneity. To address these challenges, we used DNA-fingerprinting data and Marginal Treatment Effect (MTE) framework to analyze adoption and impacts of adopting improved groundnut varieties (IGVs) in Northern Nigeria. DNA-fingerprinting results showed 57% adoption rate compared to 45% self-reported by farmers. About 29% of the sampled farmers made type I error (mistaking local varieties for improved varieties) while 44% made type II error (mistaking improved varieties for local varieties). Formal sources of seed information and empowering agricultural extension to reach more farmers was significant in ensuring accurate variety identification. Further, adopting IGV significantly reduced poverty gap and poverty severity, especially among households headed by females, older persons, lowly educated and those with limited access to credit. Therefore, policy options that enhance adoption of IGVs will significantly help in reducing poverty.

Key words: Groundnut; Variety adoption; DNA fingerprinting; Poverty; Nigeria

1. Introduction

Majority of sub-Saharan Africa (SSA) population live in rural areas and experience extreme poverty and other welfare deprivations. Most of these households derive their livelihoods from agriculture and their welfare deprivation is normally associated with poor agricultural productivity. Several, empirical studies have linked this low agricultural productivity to persistent use of archaic farming technologies (Alwang et al., 2019; Langyintou 2020). This is despite existing evidence showing that adoption of modern farming technologies like improved crop varieties can significantly increase productivity, improve food and nutrition security, and reduce poverty (Kassie et al., 2011; Manda et al., 2019). The welfare of farm households adopting improved crop varieties is expected to improve through increased availability of food from own production and additional cash income from marketable surplus. Indirect positive effects/impacts of adoption include reduced food prices for net food buyers and increased employment emanating from value addition and other backward and forward linkages along the commodity value chains. However, adoption of these improved farming technologies remains low and farming households in SSA continue living in an environment of deprived welfare outcomes.

Reasons for low adoption of improved crop varieties and impacts of these varieties on household welfare outcomes like poverty, food and nutrition security have been analyzed extensively across SSA region (Pannell and Zilberman 2020). However, majority of these past empirical studies were based on farmers self-reported adoption status which is susceptible to errors due to farmers' inability to correctly identify varieties planted over long periods of time (Marieda et al., 2016; Floro et al, 2018; Kosmowski et al., 2019; Wineman et al., 2020). In addition, agricultural seed production and delivery systems in SSA are weak and poorly regulated, especially for legumes, leading to rampant seed adulteration (Mulesa et al., 2021). Besides, weak, and poorly resourced extension system makes access to proper information about agricultural technologies difficult (Wossen et al., 2019; Muricho et al., 2021). Also, lack of clear morphological differences between crop varieties makes it hard for farmers to visually differentiate varieties (Poets et al., 2020). Even literate and knowledgeable farmers are likely to inadvertently misidentify varieties due to seed adulteration and morphological similarities. Yet accurate identification of crop varieties is critical in estimating and assessing adoption.

To address these problems associated with variety misidentifications, use of DNA–fingerprinting (DNA-FP)[1] data is slowly but steadily gaining popularity as a gold standard for tracking crop variety adoption (Floro et al., 2018; Wossen et al., 2019; Jaleta et al., 2020; Poets et. al., 2020; Wineman et al., 2020; Opata et al., 2021; Euler et al. 2022). This has been made possible due to technological breakthroughs that have made it affordable to extract and analyze DNA from crop samples in laboratories using Diversity Arrays Technology (DArT) for DNA analysis and sequencing (Yigezu et al., 2019; Jaleta et al. 2020; Poets et al., 2020;). In this DNA-FP process, the genetic material from

[1] This is the process of using DNA information to characterize the genetic material of crops planted in farmers' fields (Poets et al., 2020)

each sample is extracted, analyzed, and results matched to those in a scientifically established reference library[2] within acceptable tolerance/similarity levels.

To date, available empirical studies that used DNA-FP data have shown significant differences between farmers' self-reported and confirmed adoption levels using DNA-FP (Euler et al., 2022). Some have shown underestimation of adoption by farmers (Marieda et al, 2016; Wossen et al., 2019) while others have shown overestimation (Floro et al., 2018; Opata et al., 2021). This means that contextualized crop specific studies are needed because one-size-fits all approach may not be appropriate. Therefore, we addressed this knowledge gap by analyzing adoption and impact of improved groundnut varieties on household poverty among smallholder groundnut farmers in Nigeria using DNA-FP data. Groundnut is very important in livelihoods of smallholder farmers in Northern Nigeria and the whole country in general. According to available statistics, Nigeria accounts for about 44% of groundnut production in west Africa, 23% of Africa's production and 13% of global production (FAOSTAT, 2021). Within the country, it is estimated that about 34% of cultivated land is under groundnut and it contributes about 23% of total household cash incomes (Ajeigbe et al., 2015).

Further, besides relying on self-reported adoption status, most past empirical studies that investigated welfare impacts of improved crop varieties (Kassie et al., 2011; Manda et al., 2019; Martey et al., 2020) were based on sample average treatment effects (ATE), average treatment effects on the treated (ATT) and average treatment effect on the untreated (ATU). However, target farmers are usually heterogenous in terms of their propensity to adopt and the way the treatment (adoption) impacts their welfare outcomes (Zhou and Xie 2019; Sarr et al., 2021). To address these challenges, we used marginal treatment effects (MTE) framework. On the other hand, poverty was estimated using the three classical Foster-Greer-Thorbecke (FGT) metrics (poverty spread, poverty depth, and poverty severity).

Therefore, this paper contributes to the small but growing literature investigating adoption and impacts of improved crop varieties using more precise DNA-FP data supported by MTE analysis to take care of heterogeneity among farmers. Besides, to the best of our knowledge, there has been no study on groundnut in SSA that used this type of data in combination with MTE analysis framework. The rest of the paper is organized as follows: - section 2 delves into data and methods used to conduct adoption and impact assessment. Results and their discussions are presented in section 3 while section 4 gives summary and conclusions.

2. Data and methods

2.1 Data

This study uses household and plot level data collected in 2017 from 1470 smallholder groundnut growers in five States of Northern Nigeria (Bauchi, Jigawa, Kano, Katsina and Kebbi). The data is complemented with DNA-FP results from groundnut grain samples collected from surveyed

[2] The reference library is a set of genetic profiles for known varieties (improved and local/unimproved).

farmers. Multi-stage sampling design was used to select survey units (households). First, five States were purposively selected because they were TL project sites[3]. The second stage involved stratified sampling of Local Government Areas (LGAs) in each of the selected State where three LGAs were randomly selected in each State. The third stage involved random sampling of 42 villages within the selected LGAs. Finally, 1470 households were randomly selected based on lists provided by village leadership. Actual data collection was conducted by trained and experienced enumerators who used a semi-structured questionnaire programmed in tablets. During household interviews, groundnut grain samples for DNA extraction were collected from each household (1470 samples). Each sample had a unique identification number that linked it to specific household that it was collected from. The samples were shipped to Australia-based Diversity Arrays Technology (DArT) for DNA extraction and analysis. A total of 1279 households with complete information on household adoption and expenditure data were used in final analysis because some households had missing values.

Based on DNA-FP results, we found that about 57% of the sampled farmers had adopted IGVs (Table 1). On the other hand, farming was the main occupation of household heads (84%) who were mainly full-time farm workers (79%) with an average farming experience of almost 23 years. IGV adopters had significantly higher proportion of household heads whose main occupation was farming and those who were full-time farm workers (Table 1). However, non-adopters had significantly higher levels of formal education and farming experience than adopters. About 63% of the surveyed households had been visited by an agricultural extension staff while 34% belonged to at least one farmer group. A significantly higher proportion of adopters had been visited by agricultural extension staff and were also members to farmer groups compared to non-adopters. However, a higher proportion of adopters had problems in accessing agricultural markets compared non-adopters (Table 1). Market access problems of adopters and their household heads having lower formal education attainments could be related to the possibility that TL project that promoted IGVs in Northern Nigeria targeted remote and more vulnerable farmers than those that had relatively better market access and well educated. This is supported by the finding showing a significantly higher proportion of adopters found in TL project intervention villages (Table 1).

Table 1 about here

Further descriptive statistics showed that about 15% and 35% of the households had accessed agricultural credit and were involved in agricultural technology trials/testing/demonstrations, respectively (Table 1). A significantly higher proportion of adopters had accessed agricultural credit and were involved in agricultural technology trials/testing/demonstrations. We also found that about 43% of the households were from villages where there was IGV seed dealers, and a significantly higher proportion of adopters came from these villages (Table 1).

2.2 Methods

We estimate and analyze the impact of adopting improved groundnut varieties (IGVs) on poverty in Northern Nigeria using cross-sectional data collected from 1279 smallholder farming

[3] TL is the acronym for Tropical Legumes Project that was funded by Bill and Melinda Gates Foundation (BMGF). The project was in three phases – Phase I (2007-2011), Phase II (2012-2014) and Phase III (2015-2018)[3] under the leadership of ICRISAT.

households. Adoption estimation is based on DNA-FP results of groundnut grain samples collected from surveyed households. Confusion matrix (CM) was used to understand farmers' ability to identify groundnut varieties. Further, multinomial logit regression model (MNL) was used to analyze the determinants of accurate variety identification among sampled households. On the other hand, poverty was estimated using Foster-Greer-Thorbecke (FGT) poverty measures (Foster et al., 1984) while impact assessment was based on marginal treatment effects (MTE) framework (Andresen 2018).

2.2.1 Confusion Matrix (CM)

Following Chicco and Jurman (2020), we used confusion matrix (CM) to estimate and compare farmers' self-reported adoption rates with DNA-FP results. CM is used to evaluate the accuracy of identification predictions based on confirmed true values of those predictions. In this study, farmers had identified/predicted groundnut varieties based on their own knowledge, while DNA-FP results were used to confirm/verify farmers self-reported variety identification. Therefore, there were two sources of binary variety predictions/identifications – from farmers' self-reported variety names and DNA-FP results. In these binary responses, CM has four main components (Table 2). First, true positives (TP) are values of IGVs that were correctly identified by farmers (λ_{11} in Table 2). Second, false positive (FP) are local varieties that were incorrectly self-reported as IGVs (λ_{01} in Table 2). This λ_{01} constitute what is called Type I error (Makhtar et al., 2011; Wineman et al., 2020). Third, false negative (FN) are confirmed IGVs that farmers incorrectly self-reported as local varieties (λ_{00} in Table 2). This erroneous identification of IGVs as local varieties (λ_{00}) is called Type II error (Makhtar et al., 2011; Wineman et al., 2020). Fourth, true negative (TN) are local varieties that were correctly self-reported (λ_{10} in Table 2). Therefore, using farmers self-reported adoption outcomes as predictions and DNA-FP as actual/true variety identification, we find that the total number of true IGV adopters in the sample is φ_{11} (Eqn 1) and true non-adopters is φ_{00} (Eqn 2). The total sample size is Φ (Eqn 3).

$$\varphi_{11} = \lambda_{11} + \lambda_{00} \qquad \text{Eqn (1)}$$

$$\varphi_{00} = \lambda_{10} + \lambda_{01} \qquad \text{Eqn (2)}$$

$$\Phi = \varphi_{11} + \varphi_{00} = \lambda_{11} + \lambda_{00} + \lambda_{10} + \lambda_{01} \qquad \text{Eqn (3)}$$

Table 2 about here

From Eqn. 1 – Eqn. 3, we find that the total number of confirmed IGV adopters based on DNA-FP analysis was φ_{11}. Therefore, from CM (Table 2), seven key descriptive metrics can be derived to assess variety identification among sampled farmers (Eqn. 4 – Eqn. 10). Eqn. 4 gives accuracy rate with which sampled households can correctly identify groundnut variety regardless of whether it is improved or local. From Eqn. 5, we get the probability of variety misidentification or misidentification rate (the converse of Eqn. 4). Further, the probability of correctly identifying an IGV is given by Eqn. 6. This is the true positivity rate also called sensitivity or recall rate (Makhtar et al., 2011). On the other hand, the probability of wrongly identifying local variety as IGV is given by Eqn. 7 (rate of committing Type I error). The probability of correctly identifying local variety is given by Eqn. 8 (also called specificity rate). Beside these statistics, precision rate is computed using Eqn. 9 and it is the probability that what was identified as IGV was indeed an IGV. Finally, prevalence rate that is derived from Eqn. 10 measures true adoption rate based on DNA-FP results.

$$Accuracy\ rate = \frac{(\lambda_{11}+\lambda_{10})}{\Phi} \quad \text{(Eqn. 4)}$$

$$Misidentification\ rate = \frac{(\lambda_{00}+\lambda_{01})}{\Phi} \quad \text{(Eqn. 5)}$$

$$True\ positivity\ rate = \frac{\lambda_{11}}{\varphi_{11}} \quad \text{(Eqn. 6)}$$

$$False\ positivity\ rate = \frac{\lambda_{01}}{\varphi_{00}} \quad \text{(Eqn. 7)}$$

$$True\ negativity\ rate = \frac{\lambda_{10}}{\varphi_{00}} \quad \text{(Eqn. 8)}$$

$$Precision\ rate = \frac{\lambda_{11}}{\tau_1} \quad \text{(Eqn. 9)}$$

$$Prevalence\ rate = \frac{\varphi_{11}}{\Phi} \quad \text{(Eqn. 10)}$$

2.2.2 Determinants of groundnut variety identification

From Table 2, we find four mutually exclusive possible variety identification outcomes (TP; FP; FN and TN) that form a set of four dependent variables (Y). We analyzed the probability of a household falling into one of the four outcomes using multinomial logistic regression model (MNL). In MNL model, the dependent variable is nominal (has more than two outcomes that are not ordered). Each of these four dependent variables (Y_i) is defined by a binary outcome (1=yes; 0=otherwise). If the dependent variable has j categories, where j is a positive integer and $j \geq 3$, then MNL model is used with one category designated as the base/reference group/category. On the other hand, independent variables set (X_i) are household characteristics that condition the probability of identifying groundnut variety correctly (improved or local) or incorrectly (type I error or type II error). Therefore, the MNL model is specified as follows: -

$$P_{ij} = \beta_i X_i + e_i \quad \text{(Eqn. 11)}$$

Where P_{ij} is the probability of household i correctly or incorrectly identifying the variety it grew. Subscript j in P_{ij} denotes the four exclusive variety identification categories. The X_i are household characteristics that determine its variety identification probability. On the other hand, e_i are normally distributed error terms with zero mean and constant variance. Therefore, the probability of a household identifying groundnut variety is specified as follows: -

$$Prob\ (P_i = j) = \frac{e_{z_j}}{\sum_{k=0}^{j} e_{z_k}} \quad \text{(Eqn. 12)}$$

Where z_j is self-reported groundnut variety and z_k are alternative variety identification outcomes. Given the alternative reporting options for the farmer, log odds ratio for the realized reporting is computed as follows: -

$$\ln\left(\frac{P_{ij}}{P_{ik}}\right) = \alpha + \beta_i X_i + e_i \quad \text{(Eqn. 13)}$$

Where P_{ij} is the probability of identifying the variety as self-reported and P_{ik} are probabilities for alternative variety identification. $\ln\left(\frac{P_{ij}}{P_{ik}}\right)$ is the natural log of probability of reporting the variety as j relative to the probability of other variety reporting, k. The constant in Eqn. 13 is α while β is a vector of parameters to be estimated. Since coefficients of MNL model only gives the direction of influence of the independent variable on the dependent variable (correlates), marginal effects of each independent variable are computed to give actual magnitude of the effect of the independent variable on dependent variable. These marginal effects from MNL model are computed as follows: -

$$\delta = \frac{\partial P_i}{\partial X_i} = p_i\left(\beta_j - \sum_{k=0}^{j} P_i \beta_k\right) = P_i\left(\beta_j - \beta\right) \quad \text{(Eqn. 14)}$$

2.2.3 Poverty measures

The FGT poverty measures (poverty headcount, poverty gap and poverty severity) are widely applied indices of decomposing and comparing poverty across population groups. These three poverty measures are computed as follows: -

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{(Z-Y_i)}{Z}\right)^\alpha \quad \text{(Eqn. 15)}$$

Where N is the sample size; Z is the defined poverty line; Y_i is poverty outcome measure of the i^{th} household; $(Z - Y_i)$ is the poverty gap while α is the poverty aversion parameter that can take up three values (0, 1 and 2). When $\alpha = 0$, then P_α becomes poverty headcount. Poverty headcount is the proportion of the population that is poor (proportion of the population that is below the defined poverty line). However, this poverty headcount does not indicate how poor the poor are or how far away the poor are from the defined poverty line. On the other hand, if $\alpha = 1$, then P_α becomes poverty gap (poverty depth or intensity). Poverty gap measures how far below the poverty line are the poor and it is computed over the entire sample with those on or above the defined poverty line being assigned a poverty gap of zero. But still, poverty gap does not measure poverty distribution (inequality) among those classified as poor. Therefore, lastly, if $\alpha = 2$ then P_α becomes poverty severity. Poverty severity is the square of the poverty gap and it measures the inequality that exists among the poor. To compute these FGT poverty measures, a poverty line is needed. In this study, we followed past empirical literature (Mada and Menza 2016; Apata et al., 2018) to define a local poverty line that is based on two thirds of the average annual per capita household expenditure of the whole sample.

2.2.2 Marginal treatment effects

We estimated marginal treatments effects (MTE) following generalized discrete choice model (Roy 1951; Heckman and Vytlacil 2005). MTE is a binary treatment potential outcome framework which models how impact outcome variable varies because of selection bias due to heterogeneity in treatment uptake. In this framework, the treatment/selection model is IGV adoption status (D) which can formally be modelled as a latent variable I_D defined by observables (Z) and unobservable resistance to treatment (V) variables (Eqn. 16).

$$I_D = f_D(Z) - V \quad \text{(Eqn. 16)}$$

$$D = \begin{cases} 1 \; if \;\; \propto_0 + \propto_1 X > V \\ 0 \; if \;\; \propto_0 + \propto_1 X \leq V \end{cases} \quad \text{(Eqn. 17)}$$

Where subscript $D = 1$ if study subject is treated and $D = 0$ if otherwise. Similarly, Z is a vector of observed covariates determining the treatment regime and includes at least one extra variable that will be excluded from X of the outcome variables. This extra variable in Z is the instrument variable i.e., correlated with treatment, but independent of the outcome.

When Eqn. 17 is transformed using cumulative distribution of V to get F_V, it yields propensity score function $P(X, Z)$.

$$F_V(\propto_0 + \propto_1 X + \propto_2 Z) > F_V(V) \quad \text{(Eqn. 18)}$$

$$P(X, Z) > U_D \quad \text{(Eqn. 19)}$$

Where Eqn. 19 is a uniformly distributed random variable ranging between 0 and 1 and it represents unobserved increasing propensity of resistance to receive treatment. Therefore, individuals with propensity close to 1 are more likely not to receive the treatment compared to otherwise.

On the other hand, two outcome equations for each adoption status can be derived as follows: -

$$Y_1 = \beta_1 + \beta_{11} X + \in_1 \quad \text{(Eqn. 20)}$$

$$Y_0 = \beta_0 + \beta_{01} X + \in_0 \quad \text{(Eqn. 21)}$$

Taking expectations of these outcome functions conditional on treatment propensities, yields the following average treatment effects (ATE) and marginal treatment effects (MTE), respectively: -

$$ATE = (\beta_1 - \beta_0) + (\beta_{11} - \beta_{01}) X \quad \text{(Eqn. 22)}$$

$$MTE = ATE + E(\in_1 - \in_0) \quad \text{(Eqn. 23)}$$

To estimate MTE, assumptions must be made on the distribution of V, $\in_1$, and $\in_0$ representing the error terms of the treatment equation, outcome equation for the treated and untreated, respectively. Following Brave and Walstrum (2014), we assume trivariate normal marginal distribution with known variance-covariance matrix of V, $\in_1$, and $\in_0$. Therefore, MTE will estimate the change in outcome variable arising from infinitesimal change in propensity to get treatment. We fit generalized Roy model (Roy 1951) which runs a probit selection model and generates propensity scores and inverse mills ratio (IMR) followed by two outcome models that include the generated IMR as an additional explanatory variable to correct for selection bias (Heckman 1979).

3. Results and Discussions

3.1 Adoption rates of groundnut varieties

The DNA-FP analysis revealed that sampled farmers were growing 36 distinct groundnut varieties of which 28 (78%) were improved. Since most of the grown varieties had very low observations to support individual variety analysis, we merged improved varieties into one group and local varieties into another for subsequent binary analysis. Results from CM showed self-reported adoption rate of 45% and DNA-FP confirmed adoption rate of 57% (Table 3). This 12% adoption underestimation was statistically significant. Therefore, there exists a non-trivial variety knowledge gap among sampled households. This self-underreporting of adoption is consistent with past empirical studies (Marieda et al., 2016; Wossen et al., 2019) though it is also contrary to others that found self-overreporting of adoption (Floro et al., 2018: Wineman et al., 2020; Opata et al., 2021). Wossen et al., (2019) demonstrated that self-misreporting of adoption (type I or type II errors) may lead to biased estimation of research impacts which may result into misdiagnosis and ineffective policy options. About 29% of the surveyed farmers made type I error while 44% made type II error (Table 3). Therefore, only 56% of the 57% DNA-FP confirmed adopters had correctly identified the varieties they were growing (true positivity/recall rate), compared to 71% of the 43% DNA-FP confirmed non-adopters that were able to correctly identify the varieties that they grew (true negativity rate). Further analysis showed that variety identification accuracy rate (whether improved or local) was about 62% (Eqn. 4) while the remaining 38% was the probability of misidentification or error rate (Eqn. 5). The overall improved variety identification precision rate was about 73% (Eqn. 9).

Table 3 about here

These CM results showed that there was a significant proportion of smallholder groundnut growers in Northern Nigeria who commit type I and type II errors in groundnut variety identification. Such wrong perception (lack of information) is likely to have implications on how accompanying agronomic practices are adopted on plots where these varieties are grown (Euler et al., 2022). This misidentification can compromise the genetic potential of improved varieties that normally need better agronomic practices to achieve their yield potentials. It could also lead to misallocation of resources if high input resources are used on plots with local varieties that are genetically low yielding – leading to low returns per unit of inputs used. A combination of these two potential misidentification outcomes (compromised yield and resource misallocation) could dissuade farmers from adopting improved varieties. Pas evidence has shown that correct variety identification (TP and TN) can significantly lead to higher technical efficiency compared to incorrect identification (FP and FN) (Trinade et al. 2019). Therefore, analyzing determinants of variety misidentification among smallholder farmers is critical for designing intervention options that can induce increased adoption of improved varieties, which will lead to increased productivity and better welfare impacts of agricultural research.

3.2 Determinants of groundnut variety identification

The marginal effects results from MNL model showed that male headed households were almost 9% less likely to commit type I error compared to their female counterparts, (Table 4). This finding could be associated with easiness at which male household heads are likely to access information about improved groundnut varieties (Ankrah et al., 2020). Further, MNL results showed that increasing formal education of the household head by one year had a potential of reducing the probability of making type II error by 1% and increasing the probability of correctly identifying the local variety by 1% (Table 4). This is likely to be associated with the possibility that more educated household heads are likely to seek and scrutinize information related to the varieties that they grow compared to otherwise (Uematsu and Mishra 2010).

Table 4 about here

On the other hand, we found that households in villages that had sellers of improved groundnut seed were about 24% more likely to correctly identify improved groundnut varieties that they had grown compared to otherwise (Table 4). This finding emphasized the importance of formal seed systems in disseminating accurate information. We also find that households that accessed information on groundnut varieties from formal sources were about 13% more likely to correctly identify improved varieties that they grew and 14% less likely to commit type II error (Table 4). Similarly, engaging households in technology training increased their probability of correctly identifying improved and local groundnut varieties by about 7% and 13%, respectively (Table 4). Further, it was observed that compared to otherwise, those engaged in agricultural technology training were almost 22% less likely to make type II error. Further, households that were visited by an agricultural extension staff were about 8% more likely to correctly identify improved varieties compared to those that were not visited. Unambiguously, households that were visited by agricultural extension staff were almost 5% less likely to make type II error. We also found a positive and significant association between TL II project intervention villages and the likelihood of a household correctly identifying IGVs. This latter finding shows the importance of development projects in disseminating agricultural technology information.

3.3 Distribution of poverty headcount, depth, and severity

The average per capita annual expenditure among sampled households was about ₦ 63,329 and differed significantly between IGV adopters and non-adopters with the former having ₦ 70,464 compared to ₦ 53,751 for the latter (Table 5). Therefore, using per capita annual expenditure as a measure of poverty, we found that non-adopters are significantly poorer than adopters. This finding is consistent with past empirical work (Kassie et al., 2011; Alwang et al., 2019; Manda et al., 2019). Further, the locally developed poverty was ₦ 21,110[4] and this means that households that had annual per expenditure of less than this locally defined poverty line were considered poor, and non-poor if otherwise. It is based on this locally defined poverty line that we constructed the three FGT poverty indices (poverty headcount, poverty gap and poverty severity) following the seminal work of Foster et al., (1984).

Table 5 about here

Poverty headcount was estimated at about 32% and it did not vary significantly between IGV adopters and non-adopters (Table 5). However, per capita annual household expenditure among adopters was significantly higher than that of non-adopters. This showed skewed distribution of per capita annual household expenditure among adopters compared to non-adopters. The skewed distribution of average per capita annual household expenditure among adopters could point to the possibility that the impact of IGV adoption is heterogenous among adopting households. Also,

[4] 30% of the average per capita annual consumption expenditure following Apata et al., (2018) and Mada & Menza (2016)

while the monetary poverty line of ₦ 21,110 was far much less than the nationally established poverty line of ₦ 137,000 (National Bureau of Statistics 2020), the derived poverty headcount based on this locally defined poverty line was comparable with the national poverty headcount of about 40% (National Bureau of Statistics 2020). Reasons for lower annual per capita household expenditure in this study compared to the national figure could include the fact that the current study is based on data collected from rural farming households where it has been established that majority of the poor live and depend on farming as their main source of livelihoods (Omonona 2009). Also, the five states from which this data was collected are some of the poorest states in Nigeria (National Bureau of Statistics 2020).

Further, to know how far away the poor households were below the poverty line, we computed the poverty gap (depth) based on the defined poverty line. The estimated poverty gap was about 15% and it varied significantly across the IGV adoption regimes (Table 5). Non-adopters of IGVs had a significantly higher poverty gap (19%) than adopters (12%). Therefore, more resources are needed to move non-adopting poor households out of poverty compared to their adopting counterparts. On the other hand, poverty severity was estimated at about 9% and it was significantly higher among non-adopters (14%) compared to adopters (6%).

3.4 Impact of adopting IGVs on poverty

Selected MTE results are presented in Table 6[5]. However, before we delve into the treatment effects, we first highlight the overall distribution of MTE and ATE over the propensity to resist treatment (Figure 1). Since the MTE line of annual per capita household expenditure slopes downwards, this means that the annual per capita household expenditure is reducing in unobserved resistance to treatment (Panel A of Figure 1). On the other hand, we also find that the three FGT poverty indices are increasing in unobserved resistance to treatment (Panel B; Panel C and Panel D of Figure 1). This implies that households with high propensity to resist treatment are likely to have high poverty outcomes (headcount, gap and severity) compared to otherwise.

Figure 1 about here

Lastly, marginal treatment effect of IGVs on poverty showed that as age of the household head increased, IGV adoption had a positive and significant effect on per capita household annual expenditure, and subsequently, a significant negative effect on poverty gap and poverty severity (Table 6). Specifically, for every one-year increase in age of the household head, adopting IGVs increased per capita annual household expenditure by about 12% and unambiguously reduced poverty gap and poverty severity by 1% each (Table 6). The implication of this finding is that adoption of IGVs is more impactful in reducing poverty depth and poverty severity among the elderly, who naturally, in African context, are mainly rural inhabitants depending on agriculture/farming as a source of livelihoods, compared to younger/youths who seek off-farm employment. Similarly, by adopting IGVs, households that accessed credit increased their annual household expenditure by an overwhelming 322% and this translated into reduced poverty gap and poverty severity by about 42% and 47%, respectively. This finding is in sync with Magezi and Nakano (2020) and Nakano and Magezi (2020) who used randomized controlled trial experiments in Tanzania and found a significant positive impact of microcredit access on crop income because

[5] Detailed MTE results are available on request

of adopting improved agricultural technologies. Therefore, credit is an instrument of poverty reduction through IGV adoption pathway. These findings are critical given the increasing anecdotal evidence showing that the average age of farmers in SSA is increasing (Self Help Africa 2015; BBC 2019) and access to credit by farmers have been a challenge (Langyintou 2020).

Table 6 about here

On the other hand, compared to female headed households, adoption of IGVs by male headed households reduced per capita household annual expenditure by a whopping 279% and this resulted in significantly increased poverty headcount, poverty gap and poverty severity by 62%, 82% and 79%, respectively. This finding could be related to the possibility that female headed households are more dependent on agriculture than their male counterparts who easily venture out into more profitable non-farm income generating activities (Broeck and Kilic 2018). On the other hand, adoption of IGVs by households whose household heads were full time farm labour participants significantly increased poverty gap and poverty severity by 21% and 16%, respectively (Table 6). This later finding could be related to lack of income diversification among households whose heads are full time farm labour participants (Awotide et al., 2012).

However, one extra year of formal education by household head resulted in reduced per capita annual household expenditure by about 17% and this led to subsequent increase in poverty gap and poverty severity by about 2% each (Table 6). This finding could be associated with the possibility that more educated household heads have more lucrative off-farm employment opportunities (Broeck and Kilic 2018). Finally, adopting IGVs by households whose household heads had one more year of farming experience resulted into 16% reduction in per capita annual household expenditure and increased poverty gap and poverty severity by 1% each (Table 6).

4. Summary and Conclusions

Majority of the poor in sub-Saharan Africa (SSA) live in rural areas and mainly derive their livelihood from agriculture that is characterized low productivity and profitability. These disappointing agricultural outcomes have been associated with poor uptake of available modern farming technologies, especially improved crop varieties. However, actual adoption levels of improved crop varieties are not well known since most of the past empirical investigations have relied on farmers' self-reported adoption status that is likely to be inaccurate due to farmers' recall failure. Luckily, in recent past, there has been an emerging trend in approaches used to estimate crop variety adoption levels where crop samples are collected from farmers and subjected to DNA fingerprinting (DNA-FP) analysis to confirm the true variety identity. We adopted this innovative DNA-FP approach in our current study to estimate adoption levels of improved groundnut varieties (IGVs) in Northern Nigeria and analyzed farmers' knowledge of the varieties they were growing using confusion matrix (CM). Besides, we also adopted multinomial logistic regression to analyze determinants of farmers' ability to identify groundnut varieties. We further leveraged this DNA-FP data to analyze impacts of adopting IGVs on poverty among sampled farmers using the three Foster-Greer-Thorbecke (FGT) measures of poverty (poverty headcount, poverty gap and poverty severity) based on locally defined poverty line. Impacts of IGVs on these poverty measures were assessed using the marginal treatment effect framework because adoption and subsequent impacts were unlikely to be homogenous.

The results showed that while farmers self-reported adoption status at 45%, DNA-FP confirmed adoption was 57%. This 12% adoption underreporting showed a non-trivial variety knowledge gap. Availability of improved groundnut seed dealers in villages, formal sources of groundnut seed and groundnut variety information, engaging farmers in technology trainings and increased visits by agricultural extension staff were critical in ensuring that farmers correctly identify groundnut varieties they grew. Type I errors of variety identification could be minimized with increased visits of agricultural extension staff while type II errors could be addressed if formal education of household heads increased, more improved groundnut seed dealers are established in villages, and engage households in agricultural technology trainings. Further results showed that the average per capita annual household expenditure among sampled households was estimated at ₦ 63,329 and IGV adopters, based on DNA-FP adoption status, had significantly higher annual per capita household expenditure (₦ 70,464) compared to non-adopters (₦ 53,751). The average poverty headcount was about 32% and did not vary significantly between adopters and non-adopters. However, poverty gap and poverty severity were significantly different between adopters and non-adopters. Poverty gap was about 12% among adopters and 19% among non-adopters. On the other hand, poverty severity was 6% among adopters and 14% among non-adopters. These findings showed that poverty was spread equally among adopters and non-adopters though it was more deeply rooted and more severe among non-adopters. We also found that per capita household annual expenditure was decreasing as resistance to adoption of IGVs increased and this, unambiguously increased the three FGT poverty measures. Also, adoption of IGVs had significant effect on reducing poverty gap and poverty severity among households headed by older persons and those that had access to credit. Interestingly, we found that adoption of IGVs was significant in reducing poverty among households headed by females and those with low levels of formal education. Therefore, policy options that can enhance adoption of IGVs among these vulnerable households will significantly help in reducing poverty.

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Table 1. Descriptive statistics

Variable	Adopters (N=733)	Non-adopters (N=546)	All (N=1279)	Difference
Groundnut variety (1=Improved; 0=Local)	1.000 (0.000)	0.000 (0.000)	0.573 (0.495)	1.000***
Household head age (years)	46.319 (11.724)	46.240 (12.084)	46.285 (11.875)	0.079
Household head sex (1=Male; 0=Female)	0.926 (0.261)	0.930 (0.255)	0.928 (0.258)	-0.004
Household head main occupation (1=Farming; 0=Otherwise)	0.874 (0.332)	0.797 (0.403)	0.841 (0.366)	0.078***
Household head education level (years)	1.909 (4.416)	2.938 (5.147)	2.348 (4.767)	-1.029***
Household head farm labour (1=Full time; 0=Otherwise)	0.809 (0.393)	0.762 (0.426)	0.789 (0.408)	0.047**
Household head farming experience (years)	21.424 (12.409)	24.057 (13.099)	22.548 (12.769)	-2.632***
Household members trained in agricultural technology (1=Yes; 0=No)	0.211 (0.409)	0.212 (0.409)	0.212 (0.409)	-0.001
Household visited by agricultural extension staff (1=Yes; 0=No)	0.722 (0.448)	0.498 (0.500)	0.626 (0.484)	0.224***
Membership to farmer groups (1=Yes; 0=No)	0.360 (0.480)	0.313 (0.464)	0.340 (0.474)	0.047*
Problems in accessing agricultural markets (1=Yes; 0=No)	0.276 (0.447)	0.167 (0.373)	0.229 (0.420)	0.109***
Distance to groundnut selling point (km)	11.990 (23.387)	7.808 (12.977)	10.205 (19.733)	4.183***
Accessed credit (1=Yes; 0=No)	0.183 (0.387)	0.104 (0.306)	0.149 (0.357)	0.078***
Household head involved in agricultural technology testing (1=Yes; 0=No)	0.424 (0.495)	0.255 (0.436)	0.352 (0.478)	0.170***
Household size (number of members)	9.126 (6.349)	10.266 (6.626)	9.612 (6.490)	-1.140***
TL III project target village (1=Yes; 0=No)	0.753 (0.432)	0.520 (0.500)	0.654 (0.476)	0.233***
Seed of improved groundnut accessible within the village (1=Yes; 0=No)	0.572 (0.495)	0.231 (0.422)	0.426 (0.495)	0.341***

Figures in parentheses are standard deviations
Significance levels: *10%; **5%; ***1%

Table 2. The Confusion Matrix (CM)

Actual: DNA-FP analysis	Predicted: Farmers' self-reported identification		
	P=Positive	N=Negative	Row total
P=Positive	TP=λ_{11}	FN=λ_{00}	$\varphi_{11} = \lambda_{11} + \lambda_{00}$
N=Negative	FP=λ_{01}	TN=λ_{10}	$\varphi_{00} = \lambda_{01} + \lambda_{10}$
Column total	$\tau_1 = \lambda_{11} + \lambda_{01}$	$\tau_0 = \lambda_{00} + \lambda_{10}$	$\Phi = \varphi_{11} + \varphi_{00} = \lambda_{11} + \lambda_{00} + \lambda_{01} + \lambda_{10}$

Table 3. Comparison of farmers' self-reported and DNA-FP adoption results (confusion matrix)

Actual: DNA-FP analysis	Predicted: Farmers self-reported identification		
	Improved (N=571)	Local (N=708)	Total (N=1279)
Improved (N=733)	TP=56.207	FN=43.793	57.310
Local (N=546)	FP=29.121	TN=70.879	42.690
Total (N=1279)	44.644	55.356	100.000

Table 4. Determinants of groundnut variety identification (marginal effects of MNL model)

Variable	True Positive	False Positive (Type I error)	False Negative (Type II error)	True Negative
Household head sex (1=Male; 0=Female)	-0.021 (0.046)	-0.091*** (0.032)	0.081 (0.058)	0.032 (0.053)
Household head age (Years)	-0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
Household head formal education level (Years)	0.001 (0.002)	-0.002 (0.002)	-0.006** (0.003)	0.007*** (0.002)
Improved seed available in the village (1=Yes; 0=No)	0.235*** (0.028)	-0.002 (0.026)	-0.056 (0.036)	-0.177*** (0.037)
Number of groundnut plots	-0.003 (0.005)	0.002 (0.004)	0.000 (0.004)	0.001 (0.004)
Household head farm labour participation (1=Full time; 0=Otherwise)	-0.030 (0.029)	-0.009 (0.022)	0.015 (0.033)	0.023 (0.032)
Source of groundnut seed (1=Formal; 0=Informal)	0.129*** (0.024)	0.088*** (0.021)	-0.137*** (0.034)	-0.079** (0.035)
Household members engaged in agricultural technology training (1=Yes; 0=No)	0.065** (0.028)	0.028 (0.023)	-0.219*** (0.038)	0.127*** (0.034)
Sources of groundnut variety information (1=Formal; 0=Informal)	0.013 (0.033)	0.045 (0.030)	-0.018 (0.042)	-0.040 (0.044)
Membership to farmer groups (1=Yes; 0=No)	0.019 (0.024)	0.019 (0.019)	0.005 (0.026)	-0.042 (0.027)
Visited by agricultural extension staff (1=Yes; 0=No)	0.082*** (0.027)	-0.048** (0.022)	0.044* (0.026)	-0.078*** (0.026)
TL III project target village (1=Yes; 0=No)	0.074*** (0.027)	0.014 (0.022)	0.036 (0.027)	-0.123*** (0.026)
State	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1; values in parenthesis show standard errors

Table 5. Poverty measures

Poverty measure	Adopters (N=733)	Non-adopters (N=546)	Pooled (N=1279)	Difference
Annual per capita expenditure (₦ /year)	70,464.220 (4,661.344)	53,751.160 (2,366.770)	63,329.480 (2,864.549)	16,713.060*** (5,774.691)
Poverty headcount (proportion)	0.297 (0.017)	0.341 (0.020)	0.316 (0.013)	-0.043 (0.026)
Poverty gap (proportion)	0.116 (0.008)	0.189 (0.014)	0.147 (0.008)	-0.073*** (0.015)
Poverty severity (proportion)	0.061 (0.005)	0.138 (0.012)	0.094 (0.006)	-0.077*** (0.012)

Figures in parentheses are standard deviations
Significance levels: ***1%

Table 6. Marginal Treatment Effects of IGV adoption on poverty

Variable	Annual per capita expenditure	Poverty headcount	Poverty gap	Poverty severity
Household head age (years)	0.120*** (0.023)	-0.002 (0.008)	-0.013*** (0.004)	-0.012*** (0.003)
Household head sex (1=Male; 0=Female)	-2.793*** (0.725)	0.617** (0.249)	0.823*** (0.137)	0.791*** (0.107)
Household head main occupation (1=Farming; 0=Otherwise)	-1.312** (0.666)	0.155 (0.228)	-0.018 (0.125)	-0.042 (0.098)
Household head education level (years)	-0.172*** (0.044)	0.019 (0.015)	0.019** (0.008)	0.015** (0.006)
Household head farm labour (1=Full time; 0=Otherwise)	-0.525 (0.469)	0.154 (0.161)	0.214** (0.088)	0.161** (0.069)
Household head farming experience (years)	-0.158*** (0.024)	0.006 (0.008)	0.013*** (0.005)	0.014*** (0.004)
Household members trained in agricultural technology (1=Yes; 0=No)	-0.213 (0.658)	0.013 (0.226)	0.119 (0.124)	0.111 (0.097)
Household visited by agricultural extension staff (1=Yes; 0=No)	-0.302 (0.721)	-0.156 (0.247)	-0.175 (0.136)	-0.138 (0.107)
Problems in accessing agricultural markets (1=Yes; 0=No)	0.804 (0.543)	0.186 (0.186)	-0.097 (0.102)	-0.142* (0.080)
Membership to farmer groups (1=Yes; 0=No)	-0.080 (0.406)	-0.093 (0.139)	-0.017 (0.077)	0.017 (0.060)
Distance to groundnut selling point (km)	-0.011 (0.012)	0.004 (0.004)	-0.001 (0.002)	-0.001 (0.002)
Accessed credit (1=Yes; 0=No)	3.219*** (0.547)	-0.076 (0.188)	-0.418*** (0.103)	-0.469*** (0.081)
Household head involved in agricultural technology testing (1=Yes; 0=No)	-0.513 (0.503)	0.203 (0.173)	0.153 (0.095)	0.121 (0.074)
Household size (number of members)	0.021 (0.036)	0.014 (0.012)	0.007 (0.007)	0.003 (0.005)
TL III project target village (1=Yes; 0=No)	0.629 (0.698)	0.155 (0.239)	-0.052 (0.131)	-0.066 (0.103)
Constant	4.188*** (1.189)	-1.407*** (0.408)	-1.057*** (0.224)	-0.917*** (0.176)
ate	2.396*** (0.676)	-0.272 (0.232)	-0.515*** (0.127)	-0.467*** (0.100)
att	5.882*** (2.004)	-0.563 (0.687)	-1.124*** (0.377)	-1.024*** (0.296)
atut	-2.302* (1.357)	0.120 (0.465)	0.306 (0.256)	0.284 (0.201)
late	1.021***	-0.169	-0.251***	-0.225***

	(0.364)	(0.125)	(0.069)	(0.054)
mprte1	1.449***	-0.208	-0.353***	-0.315***
	(0.409)	(0.140)	(0.077)	(0.061)
mprte2	1.043***	-0.143	-0.278***	-0.253***
	(0.362)	(0.124)	(0.068)	(0.054)
mprte3	-0.376	-0.007	-0.030	-0.029
	(0.606)	(0.208)	(0.114)	(0.090)

Figures in parentheses are standard deviations
Significance levels: *10%; **5%; ***1%

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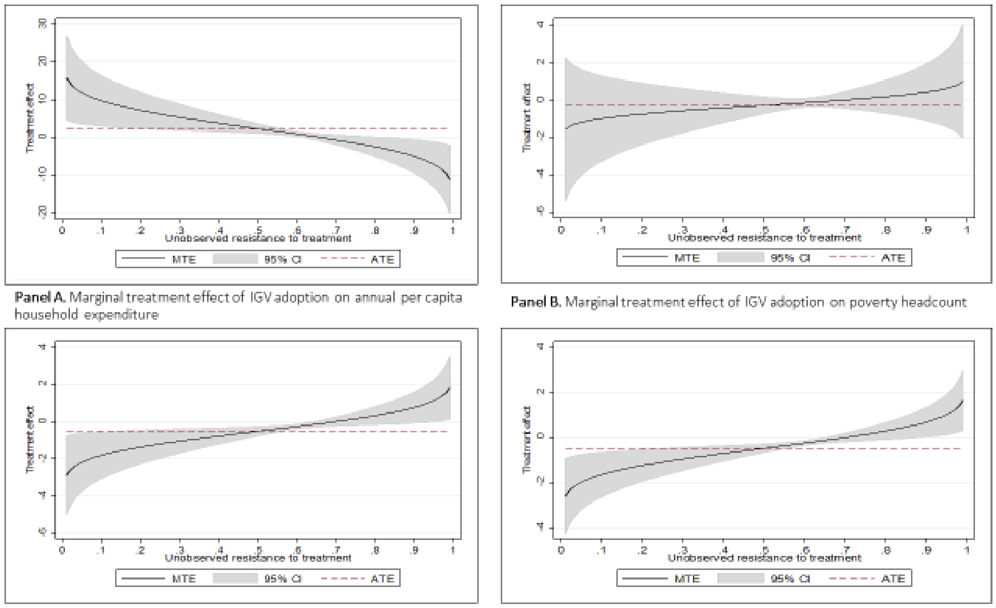

Panel A. Marginal treatment effect of IGV adoption on annual per capita household expenditure

Panel B. Marginal treatment effect of IGV adoption on poverty headcount

Panel C. Marginal treatment effect of IGV adoption on poverty gap

Panel D. Marginal treatment effect of IGV adoption on poverty severity

Figure 1. Marginal treatment effect (MTE) and average treatment effects (ATE)