Research article

Welfare impact of improved maize varieties adoption and crop diversification practices among smallholder maize farmers in Ogun State, Nigeria

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1. Introduction

In Nigeria, maize is the most commonly cultivated arable crop (Adesoji et al., 2016), it holds an important place in its food economy due to the embargo on rice and wheat flour imports (Osundare, 2013). According to FAO (2018), over the 2009–2014 period, there was an increase in harvested maize area from 3.4 to 5.9 million hectares, with an increase in production from 3.3 to 6.8 million tonnes. Currently, Nigeria’s annual maize production is about 10.5 million metric tons (Mundi Index, 2018). However, despite the evidence of the sustained maize production in the last two decades, maize yields are still low compared to its potential outcomes. Guilpart et al. (2017) revealed that on-farm maize yields are about 1–2 tons per ha compared to the possible outcomes of up to 7 tons per ha. The disparity in potential and realized yield had compelled the country to international markets to dissipate food shortage at a colossal foreign exchange expenditure.

In Ogun State, average domestic production of maize was about 272.14 metric tonnes per hectare between 2003–2007 and 343.79 metric tonnes per hectare between 2008-2015, indicating an increase of about 26 percent. The increase in maize production could be due to increasing cropping area, from 200,825 ha between 2003 -2007 to 254,202 ha in 2008–2015 period (an increase of 26 percent), and improved open pollinated and hybrid maize varieties adoption, that offer the foremost incentive for increased average yield (Adeleye et al., 2020). In comparison with other states in South-West, the average yield of 1.41 metric tons per hectare in Ogun state is the lowest (OGADEP, 2020). This is due to inadequate rainfall, poor seedlings, rudimentary farming methods, inadequate fertiliser use and pest and bird invasion (Adeleye et al., 2020).

According to the National Bureau of Statistics (2017), Nigeria’s maize import is estimated at N146.8 billion annually. However, importation policies surge inflation and discourage local production, consequently impoverishing rural livelihoods and income sources. Nevertheless, with the country’s population trends, at over 190 million between 1960 and 2017 (World Bank, 2017), and projected to double by 2050, it becomes imperative to increase maize production to meet the needs of the
ever-increasing population. Against this backdrop, technology change, which involves introducing modern agricultural technology and improved cultivation practices, becomes crucial for raising agricultural productivity (Otsuka, 2016). In this regard, the Nigerian government collaborated with International Institute of Tropical Agriculture (IITA), the International Maize and Wheat Improvement Centre (CIMMYT), and the Stress Tolerant Maize for Africa (STMA) project to develop a variety of improved maize seeds. Thus, more than 120 improved maize varieties (IMVs) with different characteristics have been released (NACGRAB 2016). IMVs are defined as a scientifically bred population that adapts to the International Union for the Protection of New Plant Varieties (IUPV) standards of being distinct, uniform, and stable (Bellon et al., 2006). Some of the improved maize varieties in Nigeria include DMR-LSR-Y, DMR-LSR-W, DMR-ESR-Y, SUWAN-1-SR-Y, 8644-3, 8644-27 and 8644-32. These enhanced varieties are sourced from, research institutes, seed companies, the National Seed Service, state agricultural supply companies, and other agro-allied retailers.

Several past empirical studies (Villano et al., 2015; Donkor et al., 2016; Ali et al., 2016; Awoide et al., 2016; Danso-Abbeam and Baiyegunhi 2019) in low-income nations especially in Sub-Saharan Africa had shown indication of the importance of agricultural technology adoption in growing farmers’ output and proﬁciency that could in turn, lead to income and livelihoods increases and improvement in other farmers’ welfare indicators. Specifically, the use of improved maize varieties (IMVs) relates to increased crop productivity, which further improves farmers’ livelihoods and fosters economic growth (Asfaw et al., 2012). Empirical observation (Ngoneu et al., 2017) have revealed that IMVs adoption provides a signiﬁcant pathway for increased productivity, increases the value of produced crops, generates rural employment, and stimulate cash ﬂow, which is expected to increase farm incomes and household welfare.

A study in South Africa by Sinyolo (2020) revealed that improved maize varieties adoption improved food security of smallholder farming households, while Manda et al. (2018) showed that improved maize varieties adoption caused positive food security gains in Tanzania and Zambia. Furthermore, in Ghana, drought-tolerant maize varieties adoption has resulted in a substantial growth in productivity and farmers' welfare (Martey et al., 2020). Additionally, other studies conducted in East African countries (Kassie et al., 2011, 2014; Bezu et al., 2014; Coromaldi et al., 2015) have shown that improved cereal crop varieties adoption increases farmers’ productivity, net farm income, per capita consumption expenditure and food security status.

However, the adoption of IMVs might require suitable complementary practices to aid better performance. For instance, Thierfelder et al. (2015) argued that yield beneﬁts often depend on the combined implementation of different improved farming methods. In light of this, resource-poor farmers adopt low-risk technologies or practices that require little cash expenditures to decrease ﬁnancial risks (Hintze et al., 2003) such as crop diversiﬁcation (CD). CD is a process where farms diversify their activities to produce several crops for sale at different times of the year. Crop diversity provides a broader choice in crop varieties production in a particular area in the pattern of rotations and or intercropping. This farming practice entails the exploration of the mutually beneﬁcial interactions among different crops belonging to the same or different species in the form of crop rotations (temporal diversiﬁcation) or intercropping (spatial diversiﬁcation) (Makate et al., 2016), which ensures continuous maximisation of returns to allocated input resources and farm income (Martin and Lorenzen, 2016). In Nigeria, maize production involves two major cropping systems: sole-cropping and crop diversiﬁcation (crop rotation and inter-cropping). However, rural farmers rarely practice sole cropping; maize is commonly grown in mixture with legumes, including groundnut, soybeans, and cowpea. This technique reduces the reliance on external inputs (fertilizer) as it enhances the potential of locally available resources. An empirical study (Harris and Orr, 2014) found that crop diversiﬁcation improves household welfare as it contributes to rural incomes and creates employment opportunities.

Unfortunately, despite the improvements in agricultural technologies in Sub-Saharan Africa (SSA), including Nigeria, there has been a decline in maize productivity (output per hectare) viz-a-viz the welfare of the farmers, thus raising doubts on the yield and welfare enhancing capacity these technologies under consideration. Furthermore, most of the existing studies in technology adoption impact literature has focused more on specific technology, such as improved seeds (Abdoulaye et al., 2018; Kathage et al., 2016, among others), crop diversiﬁcation (Idowu, 2014; Ogundari, 2013; Ibrahim et al., 2010, among others), neglecting the signiﬁcant effect of other complementary practices even though farmers adopt multiple technologies as complements or substitutes to address low productivity, biotic stress, poor soil fertility, and climate variability.

Even though IMVs and CD’s adoption provides signiﬁcant gains from maize production, the lack of experiential indication of the simultaneous adoption and the impacts of these systems on smallholder farmers’ welfare in Nigeria is concerning. This study thus contribute to existing adoption impact works by investigating the impact of complementary packages of IMVs and CD on smallholder maize farmers’ productivity and net farm income in Ogun State, Southwest, Nigeria, which is lacking in many adoption impact assessment literatures. Secondly, this study used rigorous investigative method that has the capacity to solve causal effect estimation problems because endogenous selection bias. Consequently, a multinomial endogenous switching regression (MESR), was used that allow for the estimation of the true impact of adoption IMVs and CD on the yields and income of adopters and non-adopters, taking care of both observed and hidden biases. The employment of proper econometric methods is vital for up-to-date and experiential farm-level policy applications. For instance, in advancing suitable farmers’ support agendas intended at enhancing agricultural innovations’ access and use.

2. Methodology

2.1. The study area, sampling, and data collection technique

This study was conducted in Ogun State, Southwestern region of Nigeria because it represents one of the signiﬁcant maize-producing states in the federation. The study area lies in the rainforest vegetation belt of Nigeria in the tropics along latitude 6° 20’ South and 7° 58’ North and longitude 2° 40’ West and 4° 35’ East along the Greenwich Meridian. Ogun state has a land area of 16,409.28 km², this is less than 2 percent of the country’s landmass (Olaoye et al., 2007). Ogun state shares borders with Lagos state and the atlantic ocean towards the south; Oyo and Osun states towards the north; Ondo state to the east, and the Republic of Benin towards the west. The rural population’s primary occupations in the study area include agriculture, where maize is the most dominant cultivated crop, produced on smallholders’ farms and frequently intercropped with vegetables, melon, yam, cassava, and some legumes.

A multistage purposive random sampling technique was used to select the respondent for the study. The Ogun State Agricultural Development Project (OGADEP), has categorised four Agricultural Development Project (ADP) zones in the state namely Ilaro, Ijebu-Ode, Abeokuta and Ikenne zones, which are further divided into blocks and cells. The first stage involved the random selection of a block from each zone i.e. Ilugun, Ijebu-Ile, Someke, and Oke-Odan blocks. Two extension cells from each block making a total of eight cells, were randomly chosen premised on the high intensity of maize production by subsistence farmers in the cells (Adejare and Arimi, 2013).

In the second stage, a list of maize farmers in the selected cells were obtained from OGADEP extension officers and this served as the sampling frame used for the study. However, it requires a statistically plausible sample of the target population to generate quantitative and qualitative results from this study. Thus, accurate sampling is crucial to minimize the potential sampling bias and inerence the population with a statistically estimable conﬁdence level.

Hence, the final stage, involves a random selection of twenty-five respondents from the list of farmers provided in the cells.
Consequently, a total of 200 smallholder farm households were involved in the survey, which was determined through the approach described by Cochran (2007) at a 95 percent confidence level and a 5 percent margin error. The sample size is proportionate to the size of the population of maize farmers listed (which range between 239 and 267 maize farmers in each cell). The sampling procedure give rise to a representative sample that was self-weighing having the same probability of choosing all the maize farmers in the study area. Also, a focus group discussions (FGDs) (each group including 2–7 members) were conducted with officers from OGADEP, farmers cooperatives, and community elders to obtain supplemental information on the production systems and validate some of the data for qualitative analyses.

This study employed the primary cross-sectional data because it is conservative regarding financial resources for data collection. Cross-sectional research involves data collection at a given point to assess a relationship between the variables (Bryman and Bell, 2007). The datasets were obtained through a structured questionnaire administered to the 120 randomly selected respondents (farming household heads) by trained and experienced enumerators that could communicate in the local language (Yoruba) with an in-depth knowledge of maize cropping systems in the study area. All the 200 listed farmers were interviewed and they gave consistent responses and thus used for the study. This study was conducted according to the guidelines and approval of the Human and Social Sciences Research Ethics Committee, University of KwaZulu-Natal (Protocol reference No: HSSREC/00001145/2020) and informed consent was obtained from all participants for this research.

### 2.2. Theoretical and conceptual framework

The study treated the adoption of IMVs and CD practices as a choice problem; thus, it used the random utility framework, following other studies (Nata et al., 2014; Danso-Abbeam et al., 2017; Issahaku and Abdul-Rahman 2018) in adoption of agricultural technology. The random utility suggests that a utility maximizing maize farmer will adopt any combination of IMVs and CD practices if the total benefit of adoption is greater than zero.

In several developing countries including Nigeria, rural farming households rarely employ a single technology but rather reflect on a portfolio of technologies and choose a specific technology package that maximises their expected utility (Kassie et al., 2015). Under this context, the adoption decisions of innovation are explained by expected utility maximisation or net return. In this paper, the assumption is that improved maize varieties (IMVs) and crop diversification (CD) practices will only be attractive to a farming household if it gives the most substantial positive net return subjected to the socioeconomic characteristics, resource endowments, and other determinants. A utility-maximizing resource-poor maize farmer, \( i \), will adopt improved maize varieties (IMVs) and crop diversification (CD) if \( L^* = U_{iA} - U_{iN} > 0 \), where \( L^* \) is a hidden (latent) variable representing the variance between rewards/returns from adoption \( U_{iA} \) and non-adoption \( U_{iN} \) of IMVs and CD. \( L^* \) can be illustrated as a function of noticeable variables as:

\[
L_i^* = \beta X_i + \epsilon_i \quad \text{with} \quad L_i^* = \begin{cases} 
1 & \text{if } L_i^* > 0 \\
0 & \text{otherwise}
\end{cases}
\]  

where \( L \) is a twofold variable that equals one (1) if a maize farming household adopt IMVs and CD and zero (0) otherwise. In this study, an adopter is any maize farmer who has cultivated at least one IMVs and crop diversified in the 2018/2019 farming season; \( \beta \) is a trajectory of restrictions (parameters) to be estimated; \( X \) is a trajectory of explanatory variables (such as the farmer’s socioeconomic and farm features); and \( \epsilon \) is the stochastic error term. It is assumed that IMVs and CD adoption holds considerable potential to increase maize productivity/yield and net farm income. If we assume that the increasing maize productivity and net farm income is a linear function of IMVs and CD adoption \( (L_i^*) \) and a trajectory of some explanatory variables \( (X_i) \), the linear regression equation can be depicted as:

\[
W_i = \varphi X_i + \delta L_i^* + \mu_i
\]  

where \( W \) represents maize yield or net farm income, \( \varphi \) and \( \delta \) are restrictions to be estimated, \( \mu \) is the stochastic error term. These specifications measure the productivity and the income effects of IMVs and CD adoption. Nevertheless, balanced identification of \( \delta \) involves random appointment of farming households to the treatment (adopters of IMVs and CD) and control groups (non-adopters of IMVs and CD). Without the random appointments, maize farming households with a relative lead in terms of observed and unobserved features may adopt IMVs and CD and thus would realize more welfare gains compared to a randomly selected maize grower. Thus, \( \delta \) in Eq. (2) would be prejudiced owing to unobservable characteristics interrelated with the adoption decision and welfare outcome variable (maize productivity/yield or net farm income).

To account for self-selection biases in impact evaluations, the propensity score matching (PSM) is the generally employed technique in the impact assessment study. Although with this approach, a higher percentage of the reference point variances among the two groups of farming households (adopters and non-adopters) is eliminated, their capacity to account for unobservable influences such as farmers’ intrinsic skills are limited. King and Nielsen (2016) further revealed that even when the selection model is unbiased and broad, PSM can raise imbalance and bias due to approximating an utterly randomized experiment. Therefore, gleaning from past empirical studies (Wekesa et al., 2018; Coulby et al., 2017), the multinomial endogenous switching regression (MESR) was used to assess the welfare impact of IMVs and CD adoption among smallholder maize farmers as it provides a solution to endogeneity problems from self-selection and evaluates the effects of both individual and combination of technologies.

### 2.3. Analytical and estimation technique

In this study, the multinomial endogenous switching regression (MESR) analysis was adopted as it employs a selection bias correction method by computing an inverse mill ratio (IMR) using a shortened normal distribution (Bourguignon et al., 2007). This approach is advantageous over other impact methodologies, including the propensity score matching (PSM) technique as it allows the formation of a counterfactual built on benefits to adopters’ and non-adopters’ characteristics (Kassie et al., 2018). It also permits the strategy set choices (treatment variables) to interact with noticeable variables and unnoticed heterogeneity, which depicts that the outcome of strategy choice is not restricted to the intercept of the outcome equations, nonetheless can likewise have a slope effect.

The MESR analysis is modelled concurrently in two steps; in the first step, the farming households’ choice of alternative complementary technology package is estimated by employing the multinomial logit (MNL) model while accounting for unobserved heterogeneity. At the same time, the IMR is also determined from the estimated probabilities in the MNL model. In the second step, the impact evaluation of the different complementary technology packages of IMVs and CD on the outcome variables using the ordinary least square (OLS) estimator with IMRs as added covariates to explain for selection bias from time-differing unnoticed heterogeneity. The detailed econometric estimation strategy and estimation of average treatment effects are discussed in subsequent sections.

#### 2.3.1. The multinomial logit regression (MNL) model

The multinomial logit (MNL) regression is an analytical method employed to assess the choice of alternative combinations of techniques in smallholder farming systems (Babulo et al., 2008). This approach involves studying the selection of various technologies amongst a choice set involving of all likely combinations. The marginal effects of farmers’ and farms’ characteristics on choice probabilities are appraised built upon estimates from an MNL choice model. The limitation of this
econometric framework lies in the fact that the functional form suggests that the choice probabilities ratio is independent of the presence of other substitutes in the choice set; if choice X is chosen over Y in the choice set (X, Y), then the introduction of a third alternative Z (X, Y, Z) should not make Y favoured over X. However, Bourguignon et al. (2007) ascertained that the parameter estimates from the MNL model are reliable and efficient, even if the independence of immaterial alternatives (IIA) assumption does not hold.

Let’s consider a rational farmer i, with a main objective of maximising utility, $T_i$ by comparing the benefits generated by $P$ alternative strategy. This rational farmer will choose bundle $a$ over any alternative bundle $p$ if there is an associated positive net benefit. Thus, $\Delta T_p = T_i - T_p > 0$ if $p \neq a$. Thus, the index function for the bundle's adoption can be specified as:

$$T^*_i = X_i\beta + \epsilon_i$$  
(3)

where $T^*_i$. The latent variable that explains the anticipated net benefits a farmer acquired from adopting the bundle $a$, $X_i$ signifies experiential covariates (socioeconomic, farm-specific, etc.), and $\beta_p$ is the parameter associated with $X_i$ that remains constant across alternatives. The parameter $\epsilon_i$ is a stochastic error term capturing inherently random choice dimensions and the unobserved features of the other options. If $C$ is the index of farmers choice of IMVs and crop diversification, then:

$$C = \begin{cases} 
1 & \text{if } T^*_i > \max (T^*_p) \text{ or } \lambda_1 < 0 \\
0 & \text{for all } p \neq a \\
a & \text{if } T^*_i > \max (T^*_p) \text{ or } \lambda_2 < 0
\end{cases}$$  
(4)

The index function in Eq. (4) implies that the $i^{th}$ farmer will adopt bundle $a$ if it offer him the greatest significant anticipated benefit than alternative combination or bundle $p$, $p \neq a; \lambda_2 = \max (T^*_i - T^*_p) < 0$ if the error term ($\epsilon_i$) is identical and independently Gumbel distributed (Bourguignon et al., 2007). Following McFadden (1973), the likelihood that an $i^{th}$ maize farmer will choose bundle $a$ can be illustrated by multinomial logit model, which is specified as:

$$P_a = P_{T_i} (\lambda_2 < 0 / z_i) = \frac{\exp(z_i\beta_a)}{\sum_{p \neq a} \exp (z_i\beta_p)}$$  
(5)

The MNL model in Eq. (5) was predicted employing the “mlogit” command in Stata Statistical Software (STATATA 16).

2.3.2. Multinomial endogenous switching regression (MESR) model

The MESR model involve estimating an Ordinary Least Squares (OLS) regression with selectivity correction to study the association between the welfare variables (productivity and net farm income) and a set of covariates ($\alpha$) for specific technology choice, i.e. $(I_1C_0), p = 1$ (non-adoption as a base category); IMVs $(I_1C_0), p = 2$; crop diversification (CD) $(I_0C_1), p = 3$; and both IMVs and crop diversification $(I_1C_1), p = 4$. The welfare equation for specific likely regime $p$ is specified as:

$$\begin{align*}
\text{Regime 1: } & A_{i1} = \beta_1\alpha_1 + \delta_1\theta_1 + \phi_{i1}, \quad \text{if } j = 1 \\
\text{Regime } P: & A_{ip} = \beta_p\alpha_p + \delta_p\theta_p + \phi_{ip}, \quad \text{if } j = p
\end{align*}$$  
(6)

where $(A_{ip})$ is the welfare indicators of the $i^{th}$ farmers in regime $p$, $\beta$ is the vectors of parameters, $(\phi_{i1})$ and $(\phi_{ip})$ are the stochastic error terms. These error terms $(\phi_{i1}, \phi_{ip})$ have distributions $E (\phi_{i1}|X, \alpha) = 0$ and $var (\phi_{i1}|X, \alpha) = \sigma_0^2$. In this case, $A_{ip}$ is observed if only bundle $p$ is adopted, wherein $\phi_{ip} > \max_{p \neq a} (\phi_{ip})$. According to Wooldridge (2002), Eq. (6) is augmented with the mean plot varying covariates (fertilizer use and labor use, soil fertility, etc.) to minimize the unobserved heterogeneity constraints. The stochastic error term $(\phi_{i1})$ is included of unobserved specific effects and a random error term. Thus, OLS estimates in Eq. (6) will be biased if the error terms of adoption $(\phi_{i1})$ and outcome $(\phi_{ip})$ equations are dependent. Hence, consistent estimates of $\beta_p$ and $\phi$ necessitates the presence of the choice correction terms in Eq. (5). In the multinomial choice scenario, there are $p - 1$ choice correction terms, one for each substitute adoption bundles. The second step of MESR with reliable estimates is expressed as:

$$\begin{align*}
\text{Regime 1: } & A_{i1} = \beta_1\alpha_1 + \sigma_1\lambda_1 + \delta_1\theta_1 + \phi_{i1}, \quad \text{if } j = 1 \\
\text{Regime } P: & A_{ip} = \beta_p\alpha_p + \sigma_p\lambda_p + \delta_p\theta_p + \phi_{ip}, \quad \text{if } j = p
\end{align*}$$  
(7)

where $\phi_{ip}$ is the disturbance term with anticipated value of zero, $\sigma$ is the covariance amongst $(\phi_{i1})$ and $(\phi_{ip})$, while $\lambda_p$ is the IMR calculated from predicted probabilities in Eq. (6). The IMR ($\lambda_{ip}$) is given as follows:

$$\lambda_{ip} = \sum_{p \neq a} \rho_p \frac{\exp(z_i\beta_p)}{\exp(z_i\beta_p)}$$  
(8)

where $\rho$ is the correlation between $(\phi_{i1})$ and $(\phi_{ip})$. The error terms have predictable zero value. There is a likelihood of heteroscedasticity in producing the regressor $\lambda_{ip}$ for the Inverse Mills Ratio, that was marked by the use of bootstrap standard errors. However, for reliable estimates of $\beta_p$, Teklewold et al. (2013) recommend the inclusion of selection instruments in the choice model (equation 6), that is automatically generated by the non-linearity of the selection model. This study used three instrumental variables, which are contacts with extension agents (yes = 1), membership of farmers association (yes = 1) and distance to market (FBO) (yes = 1), to identify the selection equation. It is assumed that the included instrumental variables directly influence IMVs and CD adoption, but can only influence the outcome indicators by adopting IMVs and CD. Following Shiferaw et al. (2014), this study establishes significance of inclusion of these instrumental variables by conducting a simple falsification test. According to Di Falco and Veronesi (2013), a variable is a valid instrument if it affects IMVs and CD equations’ choice decision but with no effect on the outcome variables. Our results indicate that the included instrumental variables are jointly statistically significant ($x^2 = 60.04 [p = 0.005]$) in the multinomial selection equation. However, the instruments are not jointly statistically significant; $F – \text{stat} = 1.53 [p = 0.2671], F – \text{stat} = 1.15 [p = 0.3247], F – \text{stat} = 0.95 [p = 0.4207]$, $F – \text{stat} = 0.10 [p = 0.9057]$ for non-adopters $(I_0C_0)$, adoption of IMVs only $(I_1C_0)$, adoption of CD only $(I_0C_1)$, and adopters of IMVs and CD $(I_0C_1)$, respectively, when productivity and net farm income are employed as outcome variables.

2.4. Estimation of the average treatment effects (ATT)

The multinomial endogenous switching regression (MESR) was employed to compute the average treatment effect (ATT) on the treated by comparing the predicted values of the outcome of the treated (adopters) and untreated (non-adopters) in real (actual) and unreal (counterfactual) situations. The ATT is defined as the change in the outcome variable of interest attributed to IMVs and CD's adoption only. Following Khojane et al. (2015), the restrictive expectations for the welfare variables in both the actual and their counterfactual set-ups is specified as:

Adopters with adoption (actual),

$$E(A_{ip} | U = p; \alpha_p, \theta_p, \lambda_p) = \beta_p\alpha_p + \delta_p\theta_p + \sigma_p\lambda_p$$  
(10a)

Adopters had they decided not to adopt (counterfactuals),

$$E(A_{ip} | U = p; \alpha_p, \theta_p, \lambda_p) = \beta_p\alpha_p + \delta_p\theta_p + \sigma_p\lambda_p$$  
(10b)

Eq. (10b) defines the outcome variable weights for adopters, that could have been obtained if the coefficients on their characteristics $(\alpha_p, \theta_p, \lambda_p)$ had been equal as the coefficients on the features of the non-adopters (Kassie et al., 2018). The estimation of the MESR in Eq. (8) was used
to forecast the actual Eq. (10a), and unreal (counterfactual) Eq. (10b) predicted values of welfare outcome for a farmer that adopted technology \( p \), to estimate ATT; the difference between Eqs. (10a) and (10b), and is specified as:

\[
ATT = E(A_i|U = p, \alpha_{pi}, \theta_{pi}, \lambda_{ui}) - E(A_i|U = p, \alpha_{pi}, \theta_{pi}, \lambda_{ui})
\]

\[= \alpha_{pi}(\beta_p - \beta_i) + \theta_{pi}(\rho_p - \beta_i) + \lambda_{ui}(\rho_p - \sigma_i) \tag{11}\]

On the right-hand side of Eq. (11) the first term \( (\alpha_{pi}) \) will capture the anticipated change in the average outcome variable if adopters had similar features with non-adopters. While the third term \( (\lambda_{ui}) \) alongside with the Mundlak approach \( (\theta_{pi}) \), on the right-hand side of Eq. (11) correct for selection bias and endogeneity arising from unobserved heterogeneity.

3. Empirical results and discussion

3.1. Socio-economic characteristics of the sampled maize farmers and summary statistics of the explanatory variables used in the analysis

The socio-economic characteristics and summary statistics of the explanatory variables used in the analysis of welfare impact of IMVs adoption and CD practices among smallholder maize farmers in Ogun state, Nigeria, is presented in Table 1.

From Table 1, maize farming in the study area is male-dominant. About 74 percent of the respondents were male. The mean age of the sampled respondents is 55 years, which indicates that maize production is from old (aged) household heads, while the average years of schooling of household head is about 11 years and they are well experienced in maize farming with an average of 20 years farming experience. The average annual earnings from non-farm activities of the respondents were about N4894.45. The average land holding devoted to maize farming is about 5 ha, which implies that the majority of these farmers operate on a small scale. Only about 46 percent of the sampled respondents were into livestock production, which could ensure sufficiency in labour, income, and organic matter.

A majority (98 percent) of the sampled farmers had access to extension agents, which could counteract the negative effect of lack of formal education among smallholder farming households, while about 63 percent of them are members of farmers’-based association with only a relatively few (31 percent) of them having access to credit facilities or loans. However, a majority (72 percent) of the farmers had access to improved maize seeds, and travel a mean distance of 3 km to the nearest source of improved maize seeds and about 90 percent reported using fertilisers on their maize fields even as 42 percent considered their soil fertile and 58 percent as moderately fertile and 98 percent reported having experienced drought shock.

3.2. Combination of improved maize varieties and crop diversification practices

The different combination specifications of improved maize varieties and crop diversification practices in the study area is presented in Table 2.

From the result presented in Table 1, three out of the four possible complementary combinations/packages were used by the maize farming households in the study area. About 34 percent of the farmers adopted IMVs (I1C0) only, while 15 percent of the farmer’s crop diversified (I0C1), with a relatively few (15 percent) of the rural farmers neither using any of the IMVs and CD package (I0C0). Only about 36 percent of the farmers employed both IMVs and CD package (I1C1). The result revealed that a vast majority (84.5 percent) of the respondents used packages that included at least IMVs or CD. This observation indicates the attempt by the majority of maize farming households in the study area to achieve increased maize production for household consumption and marketable surplus.

| Variables | Description | Mean | S.E |
|-----------|-------------|------|-----|
| Gender    | Dummy; 1 = male and 0 otherwise | 0.74 | 0.44 |
| Age       | Age of farm household in years | 55.46 | 13.24 |
| Educational level | Number of years of schooling | 10.71 | 5.90 |
| Farming experience | Number of years in maize production | 20.20 | 7.48 |
| Quantity of labour | Number of man-days/ha | 6.38 | 5.49 |
| Off-farm income | Amount of wages or salaries (in Naira) from off-farm activities | 4894.45 | 4365.62 |
| Land ownership | Forms of land tenancy with respect to maize farm (owned = 1, leased = 2, rent = 3, inheritance = 4) | 2.58 | 1.18 |
| Farm size | Farm land under maize production | 4.66 | 3.00 |
| Livestock ownership | Livestock herd size (in tropical livestock unit) | 0.46 | 0.50 |
| Extension contact | Yearly = 1, quarterly = 2, monthly = 3 and weekly = 4 | 0.98 | 0.12 |
| Membership of farmer-based association | 1 = if the respondent is a member of an association; 0 otherwise | 0.63 | 0.48 |
| Access to credit | 1 = if respondent received cash or input credit; 0 otherwise | 0.31 | 0.46 |
| Access to IMVs | 1 = if the respondent had access to IMVs; 0 otherwise | 0.72 | 0.17 |
| Distance to IMV seeds | Distance in km to IMV seeds | 2.53 | 1.78 |
| Fertilizer application | 1 = if the respondent applies fertilizer to the soil; 0 otherwise | 0.90 | 0.30 |
| Fertile soil | 1 = if the respondent perceived a fertile soil; 0 otherwise | 0.42 | 0.49 |
| Moderate soil fertility | 1 = if the respondent perceived a moderately fertile soil; 0 otherwise | 0.58 | 0.43 |
| Drought shock | 1 = if the respondent experienced drought stress; 0 otherwise | 0.89 | 0.31 |

3.3. Determinants of improved maize varieties and crop diversification practices

The multinomial logit model (MNL) regression results for the determinants of improved maize varieties (IMVs) and crop diversification (CD) adoption, which serves to guide the necessary interventions to improve the adoption of these technology packages, are discussed in this section and presented in Table 3.

The non-adopters of IMVs and CD (I0C0) were considered as the base category in the MNL model. The Sta RESULTS version 12 was used to generate the parameter estimates (marginal effects) of the MNL regression, which is understood as the change in forecasted probability accompanying a unit change in the exogenous variables. The sign of the marginal effect values shows the direction of the covariates’ effect on the outcome variables, while the magnitude is an indication of the probability of effects (Dano-Abbeam and Baiyegunhi, 2018). The MNL regression fits our data considerably fine. We reject the Wald test that all regression coefficients are jointly equal to zero as \( \chi^2 (41) = 83.49; p = 0.000 \). The estimated results indicate that the marginal effects vary considerably across the alternative bundles.

**The influence of age:** The estimated result in Table 2 indicated that farmer’s age was negative and statistically significant with all the alternative IMVs and CD packages implying that the likelihood of adopting IMVs only (I1C0), crop diversification only (I0C1), and IMVs and CD (I1C1) decreases as farmers get older. A plausible assumption is that as farmers advance in age, there is a rise in their risk aversion and a reduced interest
in continued investment on the farm, suggesting that older farmers may be averse to new technology (Thomas et al., 2017; Okello et al., 2019), while young farmers maybe more disposed to trying out novel technology and accept risk associated with adoption of new technology (Kinuthia and Mabaya, 2017). The results are compatible with those of Baiyegunhi et al. (2018) and Okello Okello et al., (2019) who found that households headed by older adults have a lower propensity to adopt agricultural technology.

The influence of farming experience: This variable’s estimated marginal effect exhibited a statistical significance and a positive relationship across alternative packages. That is, a year increase in farming experience increases the probability of adopting IMVs only (I,C,0), crop diversification only (I,C,1), and IMVs and CD package (I,1C,1). This result shows the significance of accumulated years of experience in maize farming as it enables farmers to make effective decisions concerning input combinations and technology adoption. This notion aligns with Ojo and Ogunyemi (2014), who reported a statistically significant positive association between increased years in farming and technology adoption.

The influence of farm size: The result from the MNL regression in Table 2 showed that an increment in farm size by a hectare (1ha) translated to an increased probability of adopting IMVs only (I,C,0) and IMVs and CD (I,1C,1). This is plausible because returns to adoption of new technologies are scale-dependent (Baiyegunhi et al., 2019), and as a result, farmers with large farm size are expected to adopt IMVs and diversify their cropping system to obtain substantial farm yields for marketable surplus and profit maximization.

The influence of membership in an association: In this study, an increased membership in farmers’-based organisations/groups could increase the probability of adopting IMVs (I,C,0) only. In rural Nigeria, farming households are constrained by inadequate insurance markets and scarce information, and under these circumstances, coupled with the perception of improved seeds to be relatively riskier, the safety net provided by membership in farmers’-based organisations/groups may increase the chances of IMVs adoption (Dercorn and Christiaesen, 2011). Another possible explanation is that social networks facilitate information exchange and farmers’ accessibility to inputs that enable adoption decisions. Baiyegunhi et al. (2019) and Ghimire and Huang (2015) observed similar results in their studies.

The influence of fertile soil: Plot-level characteristics also condition agricultural technology adoption (Baiyegunhi and Hassan, 2018). The marginal effects showed that fertile soil was negatively associated with the use of IMVs only (I,C,0), which reflects that farmers who perceived the soil for their maize crop as fertile, are more likely to preferred the use of landraces. However, the adoption of CD only (I,C,1) and IMVs and CD (I,1C,1) was positively influenced by fertile soils.

The influence of fertilizer application: The marginal effects estimate of fertilizer application indicated that the probability of adopting IMVs and CD (I,1C,1) increased with increasing fertilizer use. This is because fertilizer application in IMVs and CD (I,1C,1) package could help avoid crop production risk, as yield increasing varieties may be vulnerable to pest epidemics (Jhantami, 2011). Nonetheless, organic fertilizer is well-recognised for sustaining soil fertility in the long run, which favours crop portfolio increase.

### Table 3. The MNL model marginal effects estimates of the determinants of IMVs and CD.

| Variables                                    | I,C,0 | I,C,1 | I,1C,1 |
|----------------------------------------------|-------|-------|--------|
| **Socioeconomic characteristics**            |       |       |        |
| Gender (dummy)                               | -0.66 | 0.76  | 0.82   |
| Age of maize farmers (years)                 | -0.03 | 0.08  | -0.06  |
| Farming experience (years)                   | 0.14b | 0.14  | 0.10b  |
| Years spent schooling (years)                | -0.01 | 0.17  | -0.21  |
| Farm size (ha)                               | 0.46b | 0.36  | 0.49b  |
| Quantity of labour (man-days/ha)             | 0.26  | 0.03  | -0.29  |
| **Institutional and policy variables**       |       |       |        |
| Extension contact                            | 4.40  | 4.15  | 4.45   |
| Access to credits (dummy)                    | -0.34 | 0.23  | -0.19  |
| Membership of an association (dummy)         | 0.40b | 1.28  | -0.66  |
| Distance to market (km)                      | -0.21 | 0.41  | -0.24  |
| **Farmer’s perception variable**             |       |       |        |
| Extreme weather (dummy)                      | 0.52  | 0.31  | 0.49   |
| Fertile soil (dummy)                         | -0.53b| 0.35  | 0.75b  |
| Moderate soil fertility (dummy)              | -0.20 | 1.98  | 0.83   |
| Fertilizer application (kg/ha)               | 0.29  | 0.40  | 0.86b  |

Number of observations = 200; Wald test (χ²(41) = 83.49; p = 0.000).
Note: ME and SE represents marginal effects and standard errors, respectively. I,C,0 is the base category, a, b, and c symbolize statistical significance at 1%, 5%, and 10% probability levels, respectively.
The unconditional average effects in presented in Table 3 indicate that adopters of IMVs and CD alternative packages earn more income than non-adopters. It is also worth noting that the increased yields realized from IMVs adoption translated into increased net farm income. The ATT results revealed that an enormous income effect of N1,968/ha (5.5USD) was discovered from the adoption of IMVs (I1C0) only. The ATT results also revealed that IMVs adoption in isolation has significant increase in maize yields. This result conforms with Manda et al. (2015), who revealed that IMVs adoption in isolation has more significant effects on maize yields in Eastern Zambia.

### 3.4.2. Net farm income effect

The unconditional average effects in presented in Table 3 indicate that adopters of IMVs and CD alternative packages earn more income than non-adopters. It is also worth noting that the increased yields realized from IMVs adoption translated into increased net farm income. The ATT results revealed that an enormous income effect of N1,968/ha (5.5USD) was discovered from the adoption of IMVs (I1C0) only. The lowest income of N1,547/ha (4.29USD) was obtained from the adoption of crop diversification (I0C1) only compared to N1,871/ha (5.20USD) for the adopters of IMVs and CD (I1C1) packages. This finding is similar to Khonje et al. (2015), that showed that the adoption of ‘improved maize only’ results in significant crop incomes.

### 5. Conclusion and policy implications

This study assessed the determinant of complementary adoption of improved maize varieties (IMVs) and crop diversification (CD) and their welfare implications (measured by productivity and net farm income) among smallholder maize farmers in Ogun State, Nigeria. Results from the multinomial logit model (MNL) showed that the likelihood of a farmers adopting the IMVs and CD practices is influenced by different household socioeconomic characteristics, institutional, and input variables. The implication of this study’s findings is that policies designed at increasing the adoption of many and interdependent agricultural technologies can be designed by focusing on these factors while improving maize production and rural livelihoods in the study area. For instance, the important role of institutional variables such as contact with extension personnel and membership in a farmer-based association suggests that the Federal Ministry of Agriculture in Nigeria and the Ogun State Agricultural Development Programme (OGADEP) need to strengthen extension services through the recruitment and training of adequate numbers of technically capable service providers across the nations’ agricultural zones and local government areas of the state. The result also signifies the need to invest in public safety-net programs and the establishment and strengthening of farmer based-organization in communities/villages with dysfunctional or no farmer-based institutions.

Concerning the potential welfare impact of IMVs and CD practices, the inference drawn from this study is that farmers who use IMVs (I1C0) only were more productive and realized substantial income even when other production inputs are held constant. The results from the MESR-based average treatment effect also indicate that IMVs and CD practices improve farmers’ welfare in terms of maize productivity and net farm income. This indicates that efforts to improve productivity and rural livelihoods should focus on investments in seed-based technologies. In addition, a well-functioning community-based seed provision system should be promoted to enhance farm households’ accessibility to certified improved seeds. Furthermore, there is need for policymakers and stakeholders to improve the seed supply chain to broaden IMVs use in Nigeria.

### Declaration

**Author contribution statement**

Baiyegunhi L. J. S: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Akinbosoye F: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Bello L. O: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

### Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

### Data availability statement

The data that has been used is confidential.

### Declaration of interests statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

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