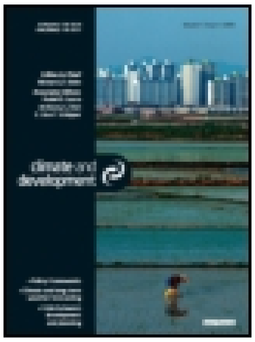

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RESEARCH ARTICLE

Evaluating the distributional impacts of drought-tolerant maize varieties on productivity and welfare outcomes: an instrumental variable quantile treatment effects approach

Kehinde Oluseyi Olagunju [a], Adebayo Isaiah Ogunniyi [b], Bola Amoke Awotide[c*], Adewale Henry Adenuga [a] and Waheed Mobolaji Ashagidigbi[d]

[a]Agri-food and Biosciences Institute (AFBI), Belfast, UK; [b]International Food Policy Research Institute (IFPRI), Abuja, Nigeria; [c]International Institute of Tropical Agriculture (IITA), Bamako, Mali; [d]Department of Agricultural Economics and Farm Management, Federal University of Technology, Akure, Nigeria

ABSTRACT

In an attempt to go beyond the conventional mean impact assessment of agricultural interventions, this paper examines the distributional impacts of adoption of drought-tolerant maize varieties (DTMVs) on the productivity and welfare outcomes of rural farming households in Nigeria. The study employed a conditional instrumental variable quantile treatment effects approach to control for selection bias that may arise from both observed and unobserved factors. The empirical findings revealed that adoption significantly impacts the distributions of maize yield and farming households' welfare. In particular, the effects of adoption are larger at the lower tails of the distributions of yield and welfare outcomes, suggesting that the strategic roles of DTMVs adoption in raising productivity and reducing poverty are better among poor farming households. These findings emphasize that effective targeting and dissemination of improved agricultural technologies are critical for increasing maize yield and improving welfare outcomes of rural farmers in Nigeria. Policy measures targeted at tackling dissemination constraints, such as the promotion of informal seed sector, may help enhance the successful dissemination and adoption of DTMVs or any agricultural intervention without masking out any sub-groups.

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Distributional impact assessment; DTMVs; livelihood; yield

1. Introduction

One of the major socio-economic concerns in developing countries is increasing poverty. The World Bank in its 2017 poverty report indicated that more than half of the extreme world poor live in the Sub-Saharan Africa (SSA) region (World Bank, 2017). The consequences of the poor state of well-being pose severe threats for human development, social peace, political stability and consequently overall economic development (Ogunniyi, Olagunju, Kabir, & Adeyemi, 2016; Upton, Cissé, & Barrett, 2016). Accordingly, the World Bank (2017) stresses the need to place the fight against poverty as a top priority agenda in the developing countries' socio-political and economic research and development plans and programmes.

Agriculture-based rural transformation is recognized to be vital not just for enhancing food security but also for supporting livelihoods outcomes, particularly for rural farming households which constitute about 75% of the world's poor (Alene, 2010; Michler, Baylis, Arends-Kuenning, & Mazvimavi, 2019). However, some agricultural production practices, for example, land intensification, tend to increase pressure on natural resources, suggesting that a reasonable attempt to sustainably feed the teeming world population requires productivity improvement (FAO et al., 2017). Climate change manifestations, such as drought, flood, melting glaciers, etc., constitute major threats to the agriculture and welfare of smallholder farmers, particularly in the rural areas of SSA countries, who have limited capacity to adapt and or to mastermind the coping strategies against these manifestations compared to mechanized and large-scale farmers (Lobell, Schlenker, & Costa-Roberts, 2011; Wheeler & Von Braun, 2013). The rural areas of SSA countries suffered more than any part of the world in terms of agricultural production reduction impact of climate change particularly drought shocks, as the production is primarily rain-fed (Shiferaw et al., 2014). According to FAO (2013), the economic losses that are drought-related as a percentage of gross national income were about 4.7% in the year 2013, tend to be higher in SSA than any other regions of the world. Similarly, Abubakar and Yamusa (2013) estimated the annual economic loss to drought in Northern rural Nigeria and found that about 330,000 metric tonne grains were lost, valued at about N15billion ($US 93.8 million).[1] Although there is a variation across regions and locations in SSA in the projections of rainfall during maize growing season, according to Cairns et al. (2013) and the Intergovernmental Panel on Climate Change (IPCC) (2007), the overall temperature has been projected to rise by 2.1–3.6°C by 2050. This may probably have an implication on the productivity of maize grains and livelihood outcomes of smallholder farmers who are, in most times, faced with cost constrains and may not able to afford costly irrigation facilities (Lobell et al., 2011).

CONTACT Kehinde Oluseyi Olagunju Kehinde-oluseyi.olagunju@afbini.gov.uk AFBI, 18a Newforge Lane, BT9 5PX Belfast, UK
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*World Vegetable Centre, Bamako, Mali

In Nigeria, maize is a staple food making up a significant portion, approximately 55%, of the population's daily diet (Nigeria Data portal, 2013). It is an important food and cash crop grown in most parts of Nigeria, especially in the Savanna zone due to the presence of high radiation which is favourable for its growth (Bello et al., 2012). Despite this recognized importance, the on-farm productivity of maize in Nigeria is still low and is still far less compared to the yields attainable in well-managed experimental plots (Shehu, Merckx, Jibrin, & Rurinda, 2018). As shown in Figure 1, the yields of maize in Nigeria have steadily lagged behind the average global yield, and since 2011 maize yields in Nigeria have been consistently lagging behind on the mean yield in Africa (FAO, 2019). The low performance of maize may be, in part, attributed to the fact that maize crop faces huge threats from climate change such as changes in the pattern of rainfall, especially in the savannah where there is large-scale production on wide arable lands. Scientific evidence, according to Daryanto, Wang, and Jacinthe (2016) and Mi et al. (2018), revealed that midseason droughts inflict more damage to maize at vegetative and reproductive phases, resulting in a yield loss of about 39.9%. In order to respond to this imminent drought threats, research and development agencies and government bodies have encouraged the development, dissemination and adoption of various "climate smart" improved agricultural technologies, with the overarching aim of providing a viable pathway for rural farming household in bolstering productivity and livelihood outcomes, coping with negative externalities and fostering farmers' resilience to climate and weather shocks (FAO, 2013; Michler et al., 2019; Wossen, Abdoulaye, Alene, Feleke, Menkir, et al., 2017). Among the notable adaptation strategies developed to cope with drought stress is the drought-tolerant maize varieties (DTMVs).Under the drought-tolerant maize for Africa (DTMA) project in 2007, the DTMVs were developed by the International Maize and Wheat Improvement Centre (CIMMYT) and the International Institute of Tropical Agriculture (IITA) in 13 countries across SSA including Nigeria, Kenya, Uganda, Ethiopia, Angola, Zambia, Zimbabwe, Mali, Benin, Mozambique, Tanzania, Ghana and Malawi. Core among the objectives of the DTMA project was to produce cultivars that can withstand drought stress conditions and also able to increase the average productivity of small farm-holders by 20–30% in 2016 (Kostandini et al., 2015; Wossen, Abdoulaye, Alene, Feleke, Menkir, et al., 2017). Besides, scientific evidence by Fisher et al. (2015) established that some of the DTMVs contain high contents of lysine and tryptophan and also have the traits of resistance against maize streak virus and enhance better tolerance to low soil nitrogen. The adoption of DTMVs will, therefore, be very essential as it might help lower associated maize production risks. Yet in rural Nigeria, as in many SSA countries, the rates of technological uptake, DTMVs inclusive, have been rather low, raising the question of whether rural farming households have been able to take advantage of the promised benefits of DTMVs adoption. For example, Lunduka, Mateva, Magorokosho, and Manjeru (2017) reported that about 35% of the sampled farmers in their study adopted improved maize varieties in Zimbabwe; 56% used improved maize varieties in rural Nigeria as reported by Abdoulaye, Wossen, and Awotide (2018); only 10–15% of area cultivated under chickpeas in 2008 in Ethiopia were covered by improved chickpea seeds (Asfaw, Shiferaw, Simtowe, & Lipper, 2012).

There is growing empirical evidence of the economic and welfare impacts of adoption of improved agricultural technologies in SSA where questions are often raised about the ability of these technologies to reduce poverty and deliver value for money by increasing farm yield. The majority of previous studies have found positive impacts of improved maize varieties on yield and households' welfare in Africa (see Wossen, Abdoulaye, Alene, Feleke, Menkir, et al. (2017) and Abdoulaye et al. (2018) for rural Nigeria; Lunduka et al. (2017) for south Eastern Zimbabwe; Ahmed, Geleta, Tazeze, and Andualem (2017) and Kassie et al. (2018) for Ethiopia; Bezu, Kassie, Shiferaw, and Ricker-Gilbert (2014) for Malawi; Khonje, Manda, Alene, and Kassie (2015) for Eastern Zambia). Similarly, Kassie, Jaleta, and Mattei (2014) and Manda, Gardebroek, Kuntashula, and Alene (2018) reported positive impacts of improved maize

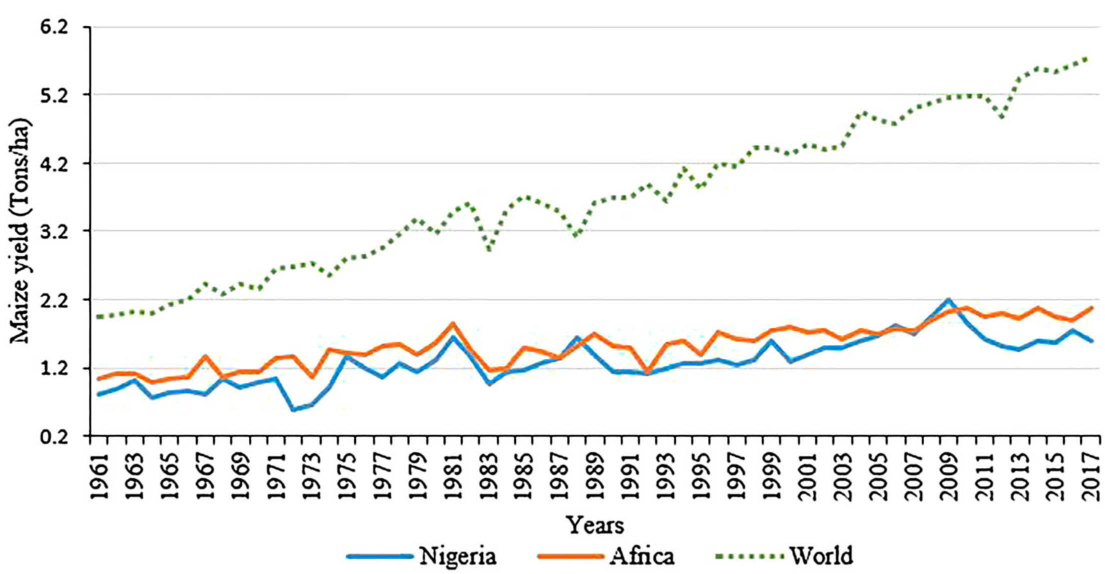

Figure 1. Maize yield trend in Nigeria, Africa and the world at large (FAO, 2019).

varieties on food security in rural Tanzania and Eastern Zambia. To the best of our knowledge, all these studies focused on the mean impacts of adoption. This is not limited to studies on the impact of improved maize varieties as about 95% of impact assessment studies have focused on overall mean impacts (Frölich & Melly, 2010). Consequently, there has been relatively little evidence on the distributional impact of adoption of improved agricultural technologies. This is rather surprising considering the likelihood that the distributions of the outcome variables may change in many ways that cannot be revealed by an examination of averages. For instance, the distribution of farmer's income inequality may increase at the upper tail while the lower tail may decrease. Kassie et al. (2014) and Ainembabazi et al. (2018) acknowledged that the impact of improved technology may vary according to the distribution of the outcome variables, suggesting that all adopters may not benefit in the same way. In this paper, we aim to fill this gap in the literature by evaluating whether the impact of adoption of DTMVs has a beneficial effect on productivity and welfare, and to what extent these benefits vary across the different segments of productivity and welfare distribution. Specifically, in this study, the distributions of productivity and welfare outcomes were segmented into five quantiles. This number of quantiles was chosen so as to effectively manage the degree of freedom within each quantile of our outcome variable for consistent estimates. Similar approach has been adopted in most studies that employed quantile regression analysis on cross-sectional dataset [for example, Issahaku and Abdulai (2019)].

Our paper has three main contributions to the literature. First, the paper provides the first attempt to explicitly evaluate the differential impacts of adoption of DTMVs on the productivity and welfare of rural farming households. The large literature on the impact of the improved maize varieties highlighted above have employed analytical techniques that are restricted to estimating the average treatment effects, and none of these studies have attempted to consider analyzing the distributional impacts which are capable of providing a more accurate picture of how adoption impacts vary across the distribution of the outcome variables such as yield and welfare. Few studies that considered this topic are in labour and conservation economics (Autor, Houseman, & Kerr, 2017; Cisneros, Zhou, & Börner, 2015). In principle, the development and dissemination of improved seed varieties, especially in developing countries, are targeted at addressing the needs of smallholder farmers. On average, the adoption of improved seeds may be beneficial to commercial farm-holders, albeit may still be ineffectual in improving the yield and welfare of smallholders who are the intended beneficiaries especially if there is imperfect targeting in dissemination. In this study, we address this issue by evaluating the distributional impacts of adoption of DTMVs. This is important to properly identify the vulnerable group(s) among the rural farmers for targeting effective extension services, improved productivity and welfare policies relevant to each group of the rural farming population. Second, the paper explores conditional instrumental variable quantile treatment effects (IV-QTEs) developed by Abadie et al. (2002) to measure the distributional impacts of DTMVs. This analytical approach is able to isolate the causal impacts of adoption along the distributions of the outcomes variables while controlling for selectively bias that arises from both observable and unobservable sources of heterogeneity. Thirdly, with the understanding that agricultural technology adoption rates are still low in Nigeria, using a probit estimation approach this study also seeks to provide insights on the farm managerial, socio-economic and plot-specific factors that can hinder or promote the adoption of DTMVs in the rural Nigeria context. The understanding of these determinants is paramount in unmasking the constraints and incentives associated with DTMVs adoption which are crucial for the strategic and effective dissemination of the DTMVs and other improved agricultural technologies in Nigeria and SSA as a whole.[2]

The remaining sections of this paper are presented as follows: in Section 2, we present the empirical estimation techniques employed in the study. Section 3 describes the data, while the estimated results are reported and discussed in Section 4. We conclude in Section 5 with relevant policy recommendations.

2. Empirical estimation techniques

Farmer's decision to adopt improved agricultural technology, such as DTMVs, is constrained by several factors, for example, the availability of information and resources (Foster & Rosenzweig, 2010). We model farming household's decision to adopt DTMVs under the assumption that most farmers are rational and risk averse, and therefore will always act to maximize expected profit. Hence, a farmer's decision to adopt the improved agricultural innovation can be seen as a constrained optimization framework in which farmer will decide to adopt DTMVs when the expected benefits associated with adoption outweigh the benefits from non-adoption (De Janvry, Dustan, & Sadoulet, 2010).

To examine the impacts of adoption of DTMVs on the distributions of productivity (measured in terms of yield) and welfare outcomes (measured in terms of per capita food expenditure and per capita total expenditure) requires an estimation technique in a quantile regression framework. In particular, we specify a conditional linear quantile model presented as follows

$$Q_i^{\tau} = X_i\gamma^{\tau} + D_i\delta^{\tau} + \mu_i, \tag{1}$$

where δ^{τ} denotes the quantile treatment effect (QTE) of adoption of DTMVs, D_i, on Q_i corresponding to the τ^{th} quantile of the distribution of the productivity and welfare outcomes (such as yield, per capita food expenditure and per capita total expenditure). X_i is a vector of observed covariates that consist of socio-economic characteristics, farm practices and other farm-specific variables; γ^{τ} is a vector of parameters of the covariates to be estimated; μ_i is the unobserved random variable or error term.

Estimating the distributional impacts of DTMVs adoption using equation (1) might lead to biased and inconsistent estimates, this is because the farmer's decision to adopt DTMVs is assumed to be exogenous. However, this assumption may not hold given that farmers self-select into DTMVs adoption and this decision may likely be endogenous (Issahaku & Abdulai, 2019). Also, there are other factors that cannot be observed (such as innate farm management skills) but affect both farmers' decision to adopt and the outcome variables, leading to inconsistent and biased estimates of γ^{τ} and δ^{τ}. To account for these estimation issues, we employ the conditional IV-QTEs approach developed by Abadie et al. (2002).[3] This approach requires the use of a valid binary instrumental variable which must fulfill exclusion restriction conditions, that is, it must be uncorrelated with the potential outcome other than through the treatment variable. In the case of our study, a valid instrument must be correlated with the farmer's adoption decision and uncorrelated with productivity and welfare outcomes. Finding a suitable instrument is not a trivial issue. Previous studies, such as Abdoulaye et al. (2018) and Shiferaw et al. (2014), have argued that access to information about improved agricultural technology is a good instrument for its adoption. We employ access to varietal information as an instrument for the adoption of DTMVs. In principle, it is reasonable to argue that farmers' access to information about maize cultivars can affect farmers' decision to adopt and use DTMVs but may not certainly affect their yields and welfare outcomes.[4]

With the assumption of the existence of a valid instrument, the empirical specification of the Abadie et al. (2002) conditional IV-QTEs model is specified as follows

$$(\hat{\beta}^{\tau}_{IV,}\ \ \hat{\delta}^{\tau}_{IV}) = \underset{\beta,\ \delta}{argmin} \sum W^{AAI}_{i} \times \rho_{\tau}\ (Q_i - X_i\beta - D_i\ \delta), \tag{2}$$

$$\text{with } W_i^{AAI} = 1 - \frac{D_i\ (1 - Z_i)}{1 - \Pr(Z = 1|X_i)} - \frac{(1 - D_i)Z_i}{1 - \Pr(Z = 1|X_i)}, \tag{3}$$

where Z is the instrumental variable (access to varietal information). The causal effect estimated is the local QTE among the compliers, that is, the group of farmers who have access to varietal information and have adopted DTMVs. By construction, the weights in equation (3) are not necessarily positive, and the minimand is not necessarily convex. Abadie et al. (2002) acknowledge this problem and suggested an alternative positive weight $W^{AAI+}_{i} = E\ (W^{AAI}|\ Q_i,\ D_i,\ X_i)$ that can be estimated using a non-parametric local linear regression. The probability $Pr(Z = 1|X_i)$ of having access to varietal information is needed to compute the weight is estimated using a local logit non-parametric estimator, as detailed in Frölich and Melly (2010). This estimation was done using *ivqte* command in STATA 13 (Frölich & Melly, 2010).

Besides the main objective of this paper, we further explore the factors influencing the decision of farmers to adopt DTMVs. In order to achieve this objective, we employed the following standard probit model

$$\Pr(D_i = 1|\ X_i\ ,\ R_i,\ Z_i) = \Phi(X_i\ ,\ R_i,\ Z_i,\ \psi) \tag{4}$$

where D_i represents farmer's decision to adopt DTMVs which takes the value of 1 if the farmer adopts DTMVs and zero if otherwise. Pr denotes probability and $\mathbf{\Phi}$ denotes the Cumulative Distribution Function. X_i represents a vector of farm managerial, socio-economic and plot-specific factors; R_i is the regional fixed effect that accounts for regional-level heterogeneity in the dissemination of DTMVs to farmers. Z_i is our instrument: access to varietal information.

3. Data and descriptive statistics

The data employed in this study were obtained from the farm household survey conducted by the International Institute of Tropical Agriculture (IITA) in Nigeria. The survey was conducted between November 2014 and February 2015, as part of IITA's effort to assess the impact of awareness and adoption of DTMVs on farmers' yield and livelihood outcomes. The data collection process in the survey involved a multistage stratified random sampling procedure across the 36 states in Nigeria to obtain nationally representative data. In the first stage of the sampling procedure, the 36 Nigerian states were divided into five homogenous sub-groups on the basis of the total land area dedicated to maize production per state. Out of the five sub-groups, 18 states were selected randomly.[5] The second stage involves the random selection of enumeration areas (EAs) in each of the 18 selected states. From the National Population Commission (NPC), the sampling frame of all the EAs in each of the state, was obtained. The total number of EAs obtained from the NPC was, thereafter, divided by the Local Government Areas (LGAs) in each of the selected state so as to obtain EAs per LGA.[6] The agricultural development programmes office in the Nigeria provided the list of all farming households producing maize for the selected EAs per LGA. Finally, from the list of all the maize farming households, five farmers were selected randomly for interview per each of the EA. Altogether, the number of farming households that form the sample size was 2305. A broad range of information on the farming household's socio-economic characteristics, yield of maize and other crops, expenditure on food and non-food items, income from maize enterprise, as well as awareness and adoption of DMTVs, were collected from the survey.

The descriptive statistics of all the variables of interest used in the study are presented in Table 1. Our main treatment variable, adoption of DTMVs, was obtained from the question "Did you plant any DTMVs in the last farming season?", where a binary variable was constructed and a farmer that had used DTMVs in one of the plots is assigned one, otherwise, value zero is assigned to such a farmer. About 36 DTMVs were developed and disseminated to rural farmers in Nigeria, including TZEEI 6, TZEEI 4, TZEEI 36, TZEEI 38, etc. (see Abdoulaye, Bamire, Wiredu, Baco, & Fofana, 2009 for the full list). The summary statistics in Table 1 reveal that about one out of every four maize farmers, approximately 25%, had used DTMVs in the planting season when the survey was carried out. We also find differences in the adoption across the six geopolitical zones in Nigeria. For instance, in the North western and North eastern part of Nigeria, the adoption rates were as high as 60%.

Our main outcome indicators are related to the productivity and welfare of rural farmers in Nigeria. Our productivity indicator is the yield of maize measured as the output of maize per hectare of land cultivated. Other relevant impact assessment studies, such as Abdoulaye et al. (2018), Wossen, Abdoulaye, Alene, Feleke, Ricker-Gilbert, et al. (2017), Wossen et al. (2018) and Ogunniyi, Olagunju, Adeyemi, Kabir, and Philips

Table 1 Descriptive statistics by adoption status for DTMVs.

	Full sample	Adopters (23%)	Non-adopters (77%)	Mean diff.
Productivity and welfare outcome variables				
Yield of maize grain (kg/ha)	1153.55	1623.39	1013.45	609.94***
	(1271.04)	(1408.09)	(1192.32)	
Per capita total expenditure ('000 NGN)	105.95	106.44	105.80	0.65
	(217.29)	(198.28)	(222.70)	
Per capita food expenditure ('000 NGN)	5.42	5.48	5.40	0.08
	(8.71)	(9.84)	(8.35)	
Other covariates				
Gender of household head (1 = male; 0 = female)	0.90	0.89	0.90	−0.01
	(–)	(–)	(–)	
Age of household head (years)	48.05	47.42	48.24	−0.82
	(13.31)	(13.15)	(13.35)	
Education level of household head (years of schooling)	7.58	6.92	7.77	−0.85***
	(6.21)	(6.06)	(6.25)	
Total household size (number)	7.49	8.06	7.32	0.73***
	(4.48)	(4.07)	(4.57)	
Farming experience (years)	27.94	25.91	28.55	−2.64***
	(14.36)	(14.50)	(14.27)	
Number of years' resident in the village (years)	40.92	40.04	41.18	−1.14
	(17.06)	(17.60)	(16.90)	
Asset value of major farm equipment and household furniture('000NGN)	146.85	156.72	143.91	12.82
	(1294.70)	(1209.19)	(1319.54)	
Membership of farmers' group (yes = 1, 0 = otherwise)	0.63	0.67	0.48	0.19***
	(–)	(–)	(–)	
Access to credit (yes = 1, 0 = otherwise)	0.15	0.10	0.17	−0.07***
	(–)	(–)	(–)	
Experienced drought shock (yes = 1, 0 = otherwise)	0. 18	0.19	0.18	0.01
	(–)	(–)	(–)	
Willingness to take risk (yes = 1, 0 = otherwise)	0.72	0 .72	0.68	0.04*
	(–)	(–)	(–)	
Access to climatic information (yes = 1, 0 = otherwise)	0.53	0.51	0.54	−0.03
	(–)	(–)	(–)	
Ownership of farmland (yes = 1, 0 = otherwise)	0.86	0.91	0.85	0.66***
	(–)	(–)	(–)	
Quantity of the urea fertilizer used (kg/ha)	428.34	688.92	350.63	338.29***
	(662.67)	(836.84)	(579.06)	
Access to electricity (yes = 1, 0 = otherwise)	0.48	0.54	0.46	0.086***
	(–)	(–)	(–)	
Ownership of house (yes = 1, 0 = otherwise)	0.88	0.94	0.87	0.06***
	(–)	(–)	(–)	
House painted (yes = 1, 0 = otherwise)	0.24	0.29	0.22	0.07***
	(–)	(–)	(–)	
Roofing sheet (yes = 1, 0 = otherwise)	0.88	0.94	0.86	0.07***
	(–)	(–)	(–)	
Toilet (yes = 1, 0 = otherwise)	0.13	0.09	0.14	0.06***
	(–)	(–)	(–)	
Row planting (yes = 1, 0 = otherwise)	0.81	0.79	0.81	−0.02
	(–)	(–)	(–)	
Intercropping (yes = 1, 0 = otherwise)	0.52	0.54	0.51	0.03
	(–)	(–)	(–)	
Adoption of soil and water conservation (yes = 1, 0 = otherwise)	0.53	0.56	0.53	0.03
	(–)	(–)	(–)	
Distance to seed source (km)	17.58	17.43	17.63	0.19
	(10.06)	(9.16)	(10.32)	
Instrumental variable				
Access to varietal information (yes = 1, 0 = otherwise)	0.54	1.00	0.39	0.61***
	(–)	(–)	(–)	
Number of observations	2216	509	1707	

***$p < 0.01$.
*$p < 0$.

(2017), have used yield as a reliable measure of productivity. We find that, on average, the maize yield is 1153.55 kg/ha. But, the mean maize yield for DTMVs adopters (1623.39 kg/ha) is higher than the mean yield for non-adopters (1013.45 kg/ha) at 1% level of significance. The Kernel density graph, presented in Figure 2, shows that at the lower tail of the distribution of the maize yield, the mass of maize farmers that had not adopted the DTMVs have higher yield than those that adopted. This may be attributed to the competing effect of adoption of DTMVs on other input factors used by small-scale farmers who are mostly resource constrained. However, as the distribution moves into the upper tail, the yield of the adopters becomes higher than the non-adopters. This provides an additional reason to examine the distributional impact assessment of DTMVs adoption.

Similar to Abdoulaye et al. (2018), we employed two indicators to capture welfare outcomes. These include per capita food expenditure and per capita total expenditure. The rural farming household food consumption expenditure is defined as the monetary values of the expenditures made on food

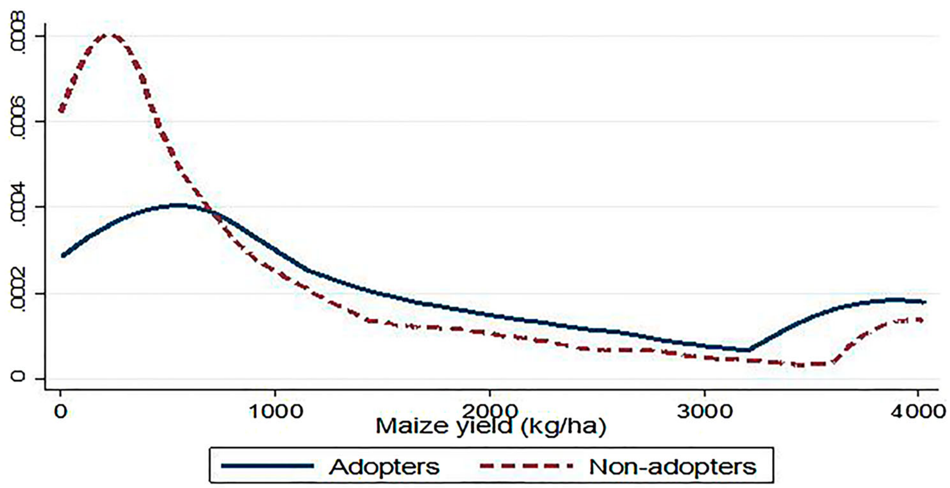

Figure 2. Kernel density of maize yield (kg/ha) by adoption status.

items. The per capita total expenditure is constructed by adding the per capita food expenditure and per capita non-food expenditure values. The use of these welfare indicators is appropriate to achieve the objective of the study being continuous variables, unlike other commonly used welfare indicators that are in binary form and are not suitable for distributional impact studies.[7] According to our data, the mean per capita total expenditure stands at about ₦ 111,500 per annum (US$ 398.21).[8] This indicates that, on average, farming household expends ₦ 305.50(US$ 1.09) per day, which is slightly below the World Bank's poverty line definition of US$ 1.25 per day at the time of the survey. The results also showed that the total per capita consumption expenditure of DTMVs adopters (₦106,440/ US$ 380.14 per annum) is slightly higher than that of non-adopters (₦ 105,800/ US$ 377.86), albeit the mean difference was not statistically significant. Looking at the second indicator of welfare, per capita food expenditure was higher among adopters but not statistically significant. Although these results may indicate a positive impact of adoption of DTMVs, caution must be taken in the interpretation as the difference observed cannot be solely attributed to DTMVs adoption.

In addition to the outcome variables, Table 1 reports the descriptive statistics of other variables included in our estimation model. We include a set of variables that captures the characteristics of farming household such as gender, age, household size, years spent in school, household size, farming experience, number of years spent in village, membership of farmers association, as well as variables that capture the wealth status of household such as the value of farm asset, ownership of house, house painted, roofing sheet and access to toilet variables. In order to account for plot-specific characteristics, we include the quantity of urea fertilizer used and farm practice variables, such as row planting, intercropping, adoption of soil and water conservation. Other covariates included are access to credit, distance to seed source, experienced drought shock, risk preferred, access to climatic information and access to electricity. These variables are included based on the assumption that they influence adoption of DTMVs and the outcome variables. For instance, the year of experience is used to proxy the level of farming experience; therefore, it is expected to positively influence the adoption of DTMVs. In the same vein, education level captures the level of farming skills needed to take advantage of the improved technology for improved yield. Some relevant impact assessment studies have found a positive effect of education on adoption level (Kassie, Jaleta, Shiferaw, Mmbando, & De Groote, 2012; Ogunniyi, Omonona, Abioye, & Olagunju, 2018). Membership of farmer's association measures the level of social capital or network of the farming households. Farmers tend to take advantage of membership in sharing of labour, securing of credit and insurance against risk (Wossen, Berger, & Di Falco, 2015). We also consider the uncertainty characteristics of agricultural production in our model by including farmers' willingness to take risk of trying new maize seed varieties measured by a binary variable with 1 if the farmers signify his willingness to take on risk, and zero if not. We find that there are statistically differences in the education level of household head, household size, farming experience, access to credit, farmland ownership, quantity of urea fertilizer used, farmer's risk preference, access to electricity and all asset ownership variables between adopters and non-adopters of DTMVs. The differences observed between the farming households that adopt DTMVs and non-adopters indicate a simple comparison and do not necessarily imply causality.

With regard to the instrumental variable employed, access to the varietal information, we find that farmers that adopted DTMVs have more access than those that do not adopt. This difference was found to be statistically significant. According to Issahaku and Abdulai (2019) and Abdoulaye et al. (2018), farmers that are aware of improved agricultural technology and therefore have access to it are likely to use it. Interestingly in our study, all the farmers that adopted had access to the varietal information, suggesting that, access to the varietal information is a good instrument for the adoption of DTMVs. To measure access to varietal information, we used a binary variable in which farmers that have access to information about new seed varieties assigned the value of one and zero if otherwise. The statistical differences persisted across the six geopolitical zones and states examined in the study. As an example, states, such as Borno, Kastina, and Zamfara where the level of adoption was very high, we have found that access to varietal information seems to be high with more than 85% having access to such information.

4. Empirical results and discussion

We present the results and discussion of our econometric estimations in this section. In Table 2, we report the results of the probit estimation of the determinants of adoption of DTMVs. Following this, we report the distributional effects of adoption of DTMVs on yield and per capita food and total expenditure in Table 3 and Table 4, respectively.

4.1. Determinants of adoption of DTMVs

In Table 2, we present the maximum-likelihood estimates of the probit regression and the average marginal effect of the adoption of DTMVs. The average marginal effects show the change in the likelihood of adoption given a unit change in the explanatory variable. The table also reports the measure of goodness of fit of our model specification which includes the Wald chi^2, Pseudo R^2 and finally the goodness of fit measure based on Archer and Lemeshow (2006). According to all the measures of the goodness of fit, we are confident to infer that the probit model specified is of a very good fit.

Table 2. Probit model estimates of determinants of DTMVs adoption.

Variable	Probit regression		Marginal effects	
	Coefficient	Std. error	dy/dx	Std. error
Gender of household head	−0.219*	0.113	−0.060*	0.033
Age of household head	0.013	0.015	0.003	0.004
Age of household head squared	−0.000	0.000	−0.000	0.000
Education level of household head	−0.008	0.006	−0.002	0.001
Total household size	0.015*	0.008	0.004*	0.002
Farming experience	0.006*	0.003	0.001*	0.001
Number of years' resident in the village	0.007***	0.003	0.002***	0.001
Asset value of major farm equipment	0.007	0.019	0.002	0.005
Membership of farmers' group	0.042	0.080	0.011	0.020
Access to credit	−0.109	0.106	−0.027	0.025
Experienced drought shock	0.161*	0.092	0.039*	0.021
Risk preferred	0.314***	0.078	0.075***	0.017
Access to climatic information	−0.057	0.071	−0.015	0.018
Ownership of farmland	−0.174	0.113	−0.047	0.032
Quantity of the urea fertilizer used	0.000**	0.000	0.000**	0.000
Access to electricity	0.174**	0.072	0.044**	0.019
Ownership of house	0.226*	0.125	0.053**	0.026
House painted	0.096	0.081	0.025	0.022
Roofing sheet	0.233*	0.125	0.054**	0.026
Toilet	0.083	0.111	0.021	0.027
Row planting	0.160*	0.088	0.042*	0.024
Intercropping	−0.014	0.069	−0.003	0.018
Adoption of soil and water conservation	0.197***	0.069	0.050***	0.017
Distance to seed source	−0.011***	0.004	−0.003***	0.001
Access to varietal information	0.233***	0.074	0.062***	0.020
North west	1.208***	0.114	0.350***	0.035
North central	0.306**	0.119	−0.072***	0.026
North east	0.788**	0.315	−0.136***	0.031
South south	−0.109	0.212	−0.026	0.049
South east	−1.372***	0.159	0.485***	0.058
Constant	−1.443***	0.450		
Wald chi^2 (30)	548.83***			
Pseudo R^2	0.23			
Goodness of fit measure (Archer and Lemeshow 2006)	0.467			
Number of observations	2216		2216	

Note: Robust standard errors reported.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

Table 3. Distributional effects of the adoption of DTMVs on maize yield ('000 kg/ha) based on Conditional IV-QTE.

	IV-QTE estimates				
	Q0.15	Q0.25	Q0.50	Q0.75	Q0.85
Treatment effect of adoption	1.718**	1.394	1.241	1.405	2.250
	(0.736)	(1.007)	(2.004)	(3.249)	(2.316)
% impact of adoption[a]	[55.86]	[38.61]	[11.56]	[5.79]	[7.07]

**$p < 0.05$.
[a]Represent percentage impact of DTMVs adoption in each of the quantile of maize yield. They were estimated as the coefficient on adoption, divided by the fitted values with adoption dummy set to zero and other covariates set to means for the treated (Abadie et al., 2002). All estimations include set of controls included in Table 2. The details are reported in Online Appendix.

Results in Table 2 indicate that male-headed households were less likely to adopt DTMVs compared to female-headed households. The probability of adopting DTMVs increased significantly with the size of the household. One likely explanation to this is that farming households with large size may have the available supply of labour for cultivation that could serve as a push factor for expansion, thereby needing to adopt improved seed varieties. This finding is in line with the results of other studies on the determinants of improved agricultural technology (Asfaw et al., 2012; Wossen et al., 2018). Opposite finding was reported in Amsalu and de Graaf (2007). The study found that farm households with a large size were less likely to adopt improved land management techniques. The study argued that farm households with a large size are mostly overburdened with a large mouth to feed, thereby engaging in other income-generating activities, such as daily labour, and the supposed readily labour supply is diverted away from agriculture, which consequently lead to little or no motivation to adopt improved agricultural technologies or other land management practices. The likelihood of adopting DTMVs increases with years of farming experience which is likely attributable to the reasoning that experienced farmers have more in-depth knowledge about the adaptive water conservation practices and other water management activities in managing drought, therefore are being proactive to adopt DTMVs in coping with potential losses due to drought. The number of years' resident in the village variable is positive and significantly associated with the farmers' decision to adopt DTMVs. Another significant push factor prompting household's decision to adopt DTMVs is their past experience of drought. This may be likely interpreted by the fact that being farmers that have stayed so long in a place have better understanding about the environmental challenges such as lack of water for irrigation purpose, thereby have higher propensity to want to adopt technologies that will help fix the problem such as the DTMVs. This is in line with the literature that new technologies are mostly adopted by those that are mostly in need of it and have suffered the consequences of not having it in the past.

Another factor that plays important role in farmers' decision on whether to or not to adopt DTMVs is risk preference. Farming households that are willing to take risk on trying new varieties are more likely to adopt while those that are averse to

Table 4. Distributional effects of the adoption of DTMVs on welfare outcomes (₦' 000) based on Conditional IV-QTE.

	IV-QTE estimates				
	Q0.15	Q0.25	Q0.50	Q0.75	Q0.85
(a) Per capita food expenditure					
Treatment effect of adoption	7.020***	7.348***	7.778**	11.258**	15.401*
	(2.145)	(2.356)	(2.938)	(4.879)	(9.273)
% Impact of adoption[a]	[80.25]	[58.02]	[31.89]	[25.67]	[26.57]
(b) Per capita total expenditure					
Treatment effect of adoption	14.564***	14.073***	20.109***	32.309***	39.420***
	(3.699)	(4.042)	(5.352)	(8.982)	(14.132)
% Impact of adoption[a]	[103.32]	[67.43]	[48.01]	[42.13]	[35.83]

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.
[a]Represent percentage impact of DTMVs adoption in each of the quantile of the welfare outcome variable. They were estimated as the coefficient on adoption, divided by the fitted values with adoption dummy set to zero and other covariates set to means for the treated (Abadie et al., 2002). All estimations include a set of controls included in Table 2. The details are reported in Online Appendix.

trying new varieties are less likely to adopt DTMVs. This may be due to weak insurance and risk management systems in rural Nigeria which tend to contribute to rural farmers' demotivation to take up DTMVs. This finding is in line with the literature which found, for instance, that one of the major hindrances to the adoption of improved agricultural technologies, like inorganic fertilizers, is risk aversion nature of African farmers (Dercon & Christiaensen, 2011). Access to infrastructure variable, proxied with access to electricity, was found to be positive and significantly affects farming household's decision to adopt DTMVs. There are two likely reasons for this relationship. First, farmers receive information on new seeds through local agricultural extension radio and television programmes, and therefore one may infer that access to electricity may help reduce constraints to information access about improved varieties and its benefits. Secondly, farming households that have poor access to infrastructures, such as electricity, roads, telecommunications, etc., may have little incentive to increase yield. Hence, they may not realize the need to adopt improved varieties like DTMVs and would rather still rely on traditional varieties that are susceptible to drought shocks.

We proxied wealth by the ownership of house, house painted, roofing sheet and toilet in line with the reasoning that rural farmers in developing countries are mostly credit constrained and this may affect the adoption. All the asset variables are positive while only roofing sheet variable was found to be significant. This suggests that households that are wealthier do have collateral to access finance which relaxes income constrained which are major disincentive to the adoption of a new technology. Ricker-Gilbert, Jayne, and Chirwa (2011) reported a similar finding in Malawi. Adoption of DTMVs is higher in farming households that practise row planting arrangement. The purpose of row planting is to enhance optimum crop yields, suggesting that such farming household would likely want to adopt DTMVs in order to maximize outputs. The adoption of soil and water conservation variable was found to be positive and significantly influence the adoption of DTMVs. This suggests farmers that adopted soil and water conservation practices are more likely to adopt DTMVs.

Our results also show the distance to seed source is another important demotivating factor affecting agricultural household's adoption decision. The marginal effect of distance to seed source variable is 0.003, suggesting that the likelihood of adopting DTMVs reduces with the distance to seed source. This implies that households that live very farther away from seed market or centres where DTMVs are available are less likely to adopt. This effect is significant at the 1%, consistent with the past literature, which found that, distance to seed markets constitute a major hindrance to adoption (Abdoulaye et al., 2018). All the regional dummies, including North West, North central, North east, South south and South east, are significantly related to the decision of farmers to adopt DTMVs but with different signs. Agricultural households in communities located in Northern regions are more likely to adopt DTMVs compared to those that have their farms in the Southern regions. The two Southern dummies enter are negative, indicating that farmers in these regions are less likely to adopt DTMVs. Our finding is consistent with the study of Ogunniyi et al. Being located in region that are susceptible to drought seems to induce the development and adoption of DTMVs in Nigeria, as the Northern part of Nigeria do have low annual rainfall between 400 and 1500 mm compared to the Southern regions that have tripled annual rainfall usually more than 2000 mm (Nigerian Meteorological Agency, 2018). In addition, having access to large commercial food markets could also be a good motivation for the adoption of DTMVs, as it is likely to be found mostly in the North central and North east regions which are historically referred to the food basket of the nation. The marginal effect and the coefficient of access to varietal information variable are found to be positive and statistically significant at the 1% level, suggesting that the excluded IV instrument employed affects the likelihood of adopting DTMVs. Agricultural households that have access to information regarding new seed varieties are more likely to adopt DTMVs, partly confirming the validity of our instruments. Similar results have been reported in the studies of (Abdoulaye et al., 2018; Wossen, Abdoulaye, Alene, Feleke, Ricker-Gilbert, et al., 2017). The likely explanation to this is that access to information about improved technology is paramount to its adoption.

4.2. The distributional impacts of the adoption of DTMVs on productivity

The distributional effects of the adoption of DTMVs on maize yield based on IV-QTE are reported in Table 3. The results show that the percentage impact of adoption of DTMVs varies across quantiles of maize yield distribution. The percentage impact of adoption is found to be the highest in the lower quantiles (Q0.15 and Q0.25), while lower estimates of the percentage impact of adoption is found in the upper quantiles (Q0.75 and Q0.85) of maize yield distribution. However, the results revealed that DTMVs only have a significant impact in the lowest quantile (Q0.15), with no statistically significant effect of the adoption found in the Q0.25, median (Q0.50) and upper quantile (Q0.75 and Q0.85). The distributional impact exhibits a downward slope curve. This suggests that farming households with low yields tend to significantly benefit more from the adoption of DTMVs in terms of percentage yield increase. This is in line with the finding of the Issahaku and Abdulai (2019) which found that farming households with lower food nutritional status benefit more from adopting climate smart practices in Northern Ghana. This finding further gives credence to the DTMA project which is aimed at bolstering productivity of rural farmers, especially farmers that operate on a small scale.

4.3. The distributional impacts of adoption of DTMVs on welfare outcomes

Table 4 reports the results of the distributional impact of DTMVs on our two welfare outcomes – per capita food expenditure and total per capital expenditure. The finding shows that, in value terms, the impact of DTMVs on per capita food expenditure is significant at all quantiles, ranging from ₦7020 at the lowest tail (Q0.15) to ₦15,401 at the highest tail (Q0.85) of the per capita food expenditure distribution, suggesting that that there is substantial heterogeneity in distributional treatment effect of DTMVs on household welfare status as proxied by per capita food expenditure. For the 15th and the 25th quantiles, the results show that DTMVs adoption significantly increases per capita food expenditure by ₦7020 and ₦7348, respectively. In terms of percentage impact of DTMVs, the findings show that the highest percentage increase of the impact of DTMVs adoption was found at the lower tails of per capita food expenditure distribution. Specifically, the adoption of DTMVs significantly raised per capita food expenditure by 80 and 58% in the 15th and the 25th quantiles, respectively. This suggests that the treatment effects of adoption on per capita food consumption expenditure are much more felt among poorer households than farming households that are well-off.

With regard to per capita total expenditure, we find that the impacts of the adoption of DTMVs is also positive and significant across the distribution of the per capita total expenditure. In value terms, the IV-QTE estimates in the part “b” of Table 4 show a significant and increasing pattern along the per capita total expenditure distribution revealing that there is substantial heterogeneity in distributional impacts of DTMVs on overall households’ welfare. The largest percentage impacts were found in the lower quantiles of the total per capita expenditure distribution. This suggests that DTMVs impacts per capita total consumption expenditure of poorer households much more than households that are well-off. This is consistent with the finding of Issahaku and Abdulai (2019) which found that food and nutrition security outcomes of poor farming households are more impacted positively by the adoption of climate smart practices in Northern Ghana than well-off farmers. Giving that farming households expend more on non-food items than on food items, the implication of the significant impact of DTMVs on per capita total expenditure is that DTMVs adoption status will have a persistent and a strong bearing on the livelihood status of rural farmers in Nigeria.

5. Conclusion

This paper analyzed the factors that influence rural farming households’ decision adopt DTMVs in Nigeria, and how adoption affects the distributions of farm productivity (measured in terms of yield) and welfare outcomes (measured in terms of per capita food expenditure and per capita total expenditure). Using the instrumental QTE approach developed by Abadie et al. (2002) that controls for selection bias that may arise from observed and unobserved factors, this paper examined the distributional effects of the adoption of DTMVs. In addition, this approach offers a clear picture of the differential effects of adoption that is concealed in the mean impacts of adoption of the improved technology which are already well documented in literature (Abdoulaye et al., 2018; Lunduka et al., 2017; Ogunniyi et al., 2017). Following Abdoulaye et al. (2018), we employ access to varietal information as an instrumental variable for proper identification of distributional impacts of adoption.

The empirical findings revealed that the impacts of adoption of DTMVs vary significantly along the yield and expenditure distributions confirming that there is significant heterogeneity in distributional impacts of DTMVs adoption. In terms of yield, a significant impact of DTMVs was observed only at the lowest tail of maize yield distribution but not significant at the middle and upper tail of the distribution. The implication of this finding is that farming households with low yields tend to significantly benefit most from adoption. The results from the analysis also revealed that the positive impacts of adoption on welfare status of farming households are much more felt among poorer households than farming households that are well-off. Our findings provide an empirical support for the notion that the development and dissemination of DTMVs is effective in addressing the low productivity of smallholder farmers especially poor households by raising their yield and welfare significantly. Notably from our results, farmers at the bottom of welfare and yield distributions had large proportional increases in yield and welfare; however, it is important to note that these farmers may also be faced with a sudden increase in costs and a lack of access to improved varieties. This, therefore, warrants that continuous support should be provided for poor farmers to reap the benefits of agricultural technology in the long term.

Finally, our findings also showed that several farm managerial, socio-economic and plot-specific factors affect farmers’ decision to adopt DTMVs. Specifically, the results highlighted these two major constraints: access to varietal information and distance from seed source. Hence, taking full advantage of the benefits of adoption requires interventions targeted at alleviating these constraints. For example, the promotion of informal seed sector may help improve access to a variety of information and input markets for improved seeds at affordable prices at the right place and time.

Notes

1. The official exchange rate was US$ 1 = 159.95 Naira on average in the study year.
2. For example, the newly initiated Climate Smart Agricultural Technologies (CSAT) project was recently launched in Mali (https://www.iita.org/wp-content/uploads/2019/04/Bulletin_2480.pdf).
3. See Supplementary Material for Abadie et al.'s (2002) theoretical framework for IV-QTEs.
4. We performed a test of validity for our instrument and the results are available on request.
5. About the 62.2% of the total land area under maize production in the country is from the selected states.
6. 10% of the LGAs were randomly selected in each of the state, and 5% of EA per LGA were selected randomly. This is based on recommendation of the National Population Commission (NPC) to ensure a nationally representative survey.
7. An example of binary indicator that is commonly used is the Foster, Greer, and Thorbecke (1984) poverty headcount line. This approach also employed per capita expenditure in its formula.
8. Using the official exchange rate at the time that the survey was carried out (1 US$ = ₦ 280).

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No potential conflict of interest was reported by the authors.

Notes on contributors

Kehinde Oluseyi Olagunju is an Agricultural Economist within the Regional Economics and Sustainability Section in the Agri-food and Biosciences Institute (AFBI), Belfast, UK. His current research focuses on developing framework for estimating productivity growth at the sector level in the UK. Prior to joining the AFBI team, Kehinde worked in several research capacities in Central Europe and Africa. He has published papers in *World Development, Economies, African Development Review*, amongst other.

Adebayo Isaiah Ogunniyi is an agricultural economist working as a Research Analyst for the International Food Policy Research Institute [IFPRI], Nigeria. His current research interests include food security and nutrition, migration dynamics, child welfare, technology adoption and innovation dynamics, social protection, spatial economics, impact assessment, rural development and agribusiness management. He is a reviewer of high impact factor journals and has good publication record in peer-reviewed journals and his work has appeared in several applied economics journals such as *World Development*, *PLOS One*, *World Development Perspectives*, *Climate and Development*, *Economies*, *Journal of Agricultural Education and Extension*, *Journal of Developing Areas*, and *International Journal of Energy Economics and Policy*. Prior to joining the IFPRI team, Adebayo worked as a Research Associate/Analyst for the Humidtropics Program (West Africa Flagship) at the International Institute of Tropical Agriculture, Ibadan, Nigeria.

Bola Amoke Awotide (PhD), a Nigerian, is currently the Monitoring, Evaluation and Learning (MEL) officer (based in Bamako, Mali) for the Climate Smart Agricultural Technologies (CSAT) project for Mali and Niger. Her academic qualifications include a bachelor's degree in Agriculture (University of Ilorin, Nigeria) with background training in agricultural economics, crop production, animal science, agricultural extension, M.Sc., and PhD in agricultural economics (University of Ibadan, Nigeria). She was a research fellow at Africa Rice Center, Cotonou, the Benin Republic/Nigeria, PhD intern-United Nations University-World Institute of Development Economics Research (UNU-WIDER), Helsinki, Finland, and academic visitor - Centre for the Study of African Economies (CSAE), Department of Economics, Oxford University, United Kingdom. Prior to joining IITA, she was postdoctoral scientist-agricultural economics at the World Vegetable Center, Bamako, Mali, Chief Agronomist for OCP Africa-Nigeria (A Moroccan multinational fertilizer company) and a consultant-agricultural economist to many international organizations such as the International Food Policy Research Institute (IFPRI). She has published in international peer-reviewed journals such as *Agricultural Economics, World Development, Food Security*, *Agricultural and Food Economics*, *Quarterly Journal of International Agriculture*, and *International Journal of Social Economics* (Emeralds). Her areas of interest include impact assessment, MEL, scaling-up of agricultural technologies, poverty and value chain analysis.

Adewale Henry Adenuga (PhD) is a Senior Agricultural Economist in the Agri-food and Biosciences Institute (AFBI), Belfast, UK. His current research focuses on investigating the economic and environmental impact of agricultural policies including their effect on the welfare and livelihood of farming households. Through his research, he provides insights into factors that influence sustainable agricultural practices among farming households and also has a keen interest in understanding those factors which impact the behaviours and actions aimed at improving farm-level safety. He has published papers in the Journal *of Environmental and Resource Economics, Ecological Economics*, *Agricultural Systems, Ecological Indicators*, amongst others.

Waheed Mobolaji Ashagidigbi (PhD) is a lecturer at the department of Agricultural and Resource Economics, Federal University of Technology, Akure, Nigeria. His research interests include issues related to welfare and health of rural households. Also, resource, production and environmental issues. He has published in *Journal of New Seeds (Journal of Crop Improvement), Journal of Biomedical Research, International Journal of Vegetable Science,* etc.

ORCID

Kehinde Oluseyi Olagunju http://orcid.org/0000-0002-5619-054X
Adebayo Isaiah Ogunniyi http://orcid.org/0000-0002-2952-2959
Adewale Henry Adenuga http://orcid.org/0000-0002-1017-2717

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