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Research article

Climate change adaptation strategies by smallholder farmers in Nigeria: does non-farm employment play any role?

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ABSTRACT

Non-farm employment in agrarian communities in developing countries has received a lot of attention. However, its role in implementing climate change adaptation strategies is rarely discussed. This study employs a cross-sectional data to examine whether rural households in Southwest Nigeria are increasing the extent of climate change adaptation practices through their participation in non-farm employment. To account for selectivity bias, the study used endogenous treatment effect for count data model (precisely Poisson) augmented with the inverse probability-weighted-regression-adjustment (IPWRA) estimator. Both estimators found that rural non-farm jobs increase smallholder farmers' adaptive capacities and that participants would have used less adaptation techniques if they had not participated in non-farm work. Efforts to boost rural development must provide more employment opportunities for farmers, particularly during the off-cropping time. This will help farmers improve their ability to adopt more climate change adaptation strategies and, consequently increase farm productivity.

1. Introduction

Crop production in Sub-Saharan Africa is heavily reliant on weather conditions, specifically rainfall. According to the IPCC (2014), the risk of instability in rainfall, temperature, and other climate parameters is increasing globally as a result of natural hazards caused by climate change. The evidence of climate change is real, and its consequences are being felt globally, with poor rural households in developing countries bearing the brunt of the burden (Asfaw et al., 2018; Gupta et al., 2019; Omerkhil et al., 2020). Many studies (Bandara and Cai 2014; Das et al., 2020) have concluded that rural farm households in developing countries are among the most vulnerable to climate change. Other empirical studies (Knox et al., 2012; Sato et al., 2020; Tumbo et al., 2020; Ureta et al., 2020) indicate that a mild rise in temperature has a negative effect on important cereal crops such as rice, maize, and wheat. Because of their reliance on rain-fed agriculture, rain-fed farmers are more likely to become victims of climate change. As a consequence, production suffers, resulting in decreased food supply and a rise in poverty. Nonetheless, climate change could have some positive effects. For example, agricultural zones that are currently less productive, such as humid forest or sub-humid agro-ecological zones, may become more productive in the future (Seo et al., 2009). Furthermore, crop productivity in the mid and high latitudes could increase by 30% by the 2050s, particularly for cereals and cool season seed crops (Olesen et al., 2007; Gornall et al., 2010). Rural households in many rural communities in Sub-Saharan Africa (SSA) are constantly changing their farm management operations in an attempt to mitigate the climate effects, the majority of which are autonomous. Many of the techniques adopted by farm households in response to climate change are focused on established information and technologies (Leclère et al., 2013; Khan et al., 2020). Farm households used several adaptation strategies to resist the various risks posed by climate change. These adaptation strategies include variation in sowing time, the use of improved crop variety (e.g., stress-tolerant variety), and shifting to new crops (Stringer et al., 2020; Ojo and Baiyegunhi 2020). Adaptation management strategies can also involve varying land size, sales of crops, mulching, application of agrochemicals, livestock rearing, mixed cropping, mono-cropping, water and soil conservation practices, among others (Challinor et al., 2014; Asfaw et al., 2018). These farm-household strategies could significantly reduce risk and, as a result, reduce the negative impact of climate change.

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The non-agricultural labour market has also been used as a critical adaptation strategy in many developing communities to withstand climate variability and change (Ito and Kurosaki 2009). This suggests the significance of non-farm employment in providing an alternative source of livelihood to households. Many studies (Davis et al., 2010; Abdulai and Huffman 2014; Sarka et al., 2017) have contributed to understanding the significance of non-farm work in farm investment and encouraging market participation. Income from non-farm work contribute significantly to total household income in many developing countries (Nagler and Naude 2017). For instance, the share of non-farm income in rural incomes in Africa, Asia, and Latin America has increased to 40–60% (Davis et al., 2010) and 44% of rural households in Africa participate in non-farm economic activities (Davis et al., 2014). Engagement in non-farm work can minimize the financial constraints of many resource-poor farm households, inducing them to purchase inputs that increase productivity of essential food crops such as rice, maize, etc.

Rice, one of the leading cereals in Nigeria, is considered crucial to the promotion of economic development, poverty reduction, famine and food insecurity, with associated activities such as production, processing, distribution and consumption (Demont and Ndour 2015). Crop production in general, and rice in particular, in Nigeria is associated with many technological, institutional, and climatic challenges. Extreme temperatures, floods, drought, and salt stress are the most common climatic issues associated with rice production. All of this is likely to worsen as the global climate changes. Drastic changes in rainfall pattern and increase in temperatures usually introduce pests and diseases as well as unfavourable conditions into the cropping calendar. These hostile conditions lead to modifications of the cropping conditions, and subsequently reduce crop productivity. Thus, rice farmers are likely to more sternly affected due to their lack of effective adaption strategies to combat the effects of climate change or variability. When productivity is low, and farmers cannot adjust fast enough to unpredictable rainfall and extreme temperature, they pay dearly for their inability to adapt. As a result, it is important that smallholder farmers be empowered to build adaptive capacities for changing weather conditions, and one way to do so is to engage in non-farm work.

Several studies on the implementation of climate change adaptation and on the determinants of participation in non-farm employment have been conducted (e.g., Arimi 2014; Asfaw et al., 2018; Asfaw et al., 2017). Moreover, a review of climate change literature (e.g., Arimi 2014; Ojo and Baiyegunhi 2020; Adeagbo et al., 2021) in Nigeria shows that the focus is more on climate change impacts, climate change modelling, perceptions, coping and adaptation strategies. However, many farm households rely on income from non-farm work to implement climate change adaptation strategies and supplement what they earned from their farms (Ojo and Baiyegunhi 2020; Yiridomah et al., 2020). While separate literature exists on adaptation strategies (e.g., Kibue et al., 2016; Mulwa et al., 2017; Abid et al., 2020; Diallo et al., 2020; Ojo and Baiyegunhi 2020) and non-farm employment (e.g., Asfaw et al., 2017; Das 2017; Giannakis et al., 2018), few of such studies have discussed the link between participation in non-farm employment and climate change adaptation strategies.

The current study contributes to literature on climate change in three ways. It first explores factors influencing farmers' decisions to participate in non-farm employment. Second, the paper discusses the factors that affect the number of climate change mitigation or adaptation strategies adopted by farming households. Finally, it assesses the impact of non-farm employment participation on the number of adaptation measures taken by farming households. Identifying the variables that explain why farmers choose an adaptation option can be helpful to policy makers in developing strategies to improve the use of effective climate change adaptation measures. It is very important to understand the link between non-farm employment and climate change because many countries in SSA, especially Nigeria, are designing and implementing climate change adaptation strategies for farmers cultivating staple crops such as rice.

The study also employs endogenous treatment effects for count data model that accounts for both observed and unobserved heterogeneity in farm household characteristics. This methodology is rarely used in agricultural literature as many impact studies (Khonje et al., 2018; Bello et al., 2020; Sinyolo, 2020; Martey et al., 2020) rely on propensity score matching or endogenous switching regression. However, in health economics, the endogenous treatment effects for count data model is commonly used when estimating the impact of a dichotomous treatment on a count data outcome (Greene 2009). For instance, the number of visits to health-care facilities (Riphahn et al., 2003; Contoyannis et al., 2004; Cameron and Trivedi 2005). In this study, we used the endogenous treatment effects for count data model employed by Bratti and Miranda (2010) to investigate how an endogenous dichotomous treatment variable (non-farm employment) affects a count outcome (number of climate change adaptation strategies) in the presence of endogenous participation.

2. Methodology

2.1. Conceptual and empirical framework

This study followed the economic theory of farm households involved mainly in rice production but can also allocate part of their time for other non-farm income-generating activities. The study employ the time allocation framework applied in the study of Issahaku and Abdul-Rahaman (2019). The central notion of this framework stemmed from the fact that farm households maximize their utility by allocating their time to three key activities; farm work, non-farm work, and leisure. This utility maximization is subject to budget constraint and that the households produced goods such as rice and purchased products are perfect substitutes. The household time constraint can be specified as $T = T_f + T_n + L$, where T_f, T_n, and Ldenote time allocated to farm production activities, non-farm work, and leisure, respectively. However, some farm households may not engage in any non-farm activity for some years, and we imposed a negative constraint on the non-farm activities such that $T_n \geq 0$.

We assess whether the involvement of farmers in non-farm economic activities would increase their ability to adopt adaptation strategies to mitigate against the negative impacts of climate change. Our hypothesis is that engagement in non-farm economic activities/employment is a deliberate strategy used by households to reduce climate change risks by implementing various types of adaptation strategies. Thus, income from non-farm jobs can be used to buy inputs such as drought-tolerant improved seeds, fertilizer, and irrigation systems, as well as to participate in other climate-change mitigation measures such as crop and livestock diversification. In the jargon of impact assessment, we would say an analysis of the impact of the selection of treatment (non-farm work) on the outcome variable. The outcome variable is the intensity of adaptation, defined as the number of measures used to minimize climate change impact. The definition of participation in non-farm employment is household wage and self-employment (e.g. petty trade, carpentry, masonry etc.) as well as other non-farm economic operations. Households that participate in any non-farm type of job is considered as participants of non-farm work and assigned a score of 1, otherwise 0.

In observational studies like this, treatment selection is usually affected by subject characteristics. Usually, farmers make voluntary decisions to engage in non-farm work based on their productive resources and demographic characteristics leading to self-selection bias. In this case, farmers' participation in non-farm employment cannot be randomly assigned. Where households are non-randomly treated, their choices for non-farm work can be influenced by their observed and unobserved characteristics that can correlate with the outcome variables. The issue of missing counterfactual data is another major econometric challenge in impact assessment. Data are missing, because the outcomes can be observed only in one state, and the counterfactuals cannot be observed for each group (Wooldridge 2003).

In the past, many applied researchers (Kassie et al., 2011; Danso-Abbeam and Baiyegunhi, 2019) have relied on the use of two main econometric frameworks namely; instrumental variable (IV) and propensity scores approach to account for confounding variables and the issue of counterfactuals. Propensity score approaches such as propensity score matching, regression adjustment and inverse probability weighting only accounts for observed heterogeneity, while IV methods account for both observed and unobserved heterogeneity. This study relies on instrumental variable Poisson regression model. The model uses the count outcome with the Poisson distribution of the error term to estimate the causal effect of participating in non-farm work on the adoption of climate change adaptation strategies. However, a double-robust estimator, inverse-probability-weighting-regression-adjustment (IPWRA) (combination of regression adjustment and inverse probability weighting estimators) (Austin 2011) was also used as a robustness check.

Our principal object of interest is to measure the average treatment effect on the treated (ATT). Takahashi and Barret (2013) defined ATT as the average difference in potential outcomes of non-farm workers with or without participation in non-farm work. Following Imbens and Wooldridge (2009) and Adolwa et al. (2019), the ATT can be expressed as;

$$ATT = E\{Y_{1j} - Y_{0j} / T_j = 1\} = E(Y_{1j} / T_j = 1) - E(Y_{0j} / T_j = 1) \tag{1}$$

where $E\{\cdot\}$denotes the expectation operator, Y_{1j} is the potential outcome for farm households who engage in non-farm work, $Y_{0j}$is the potential outcome of farm households who do not engage in non-farm work. $T_j$represents the treatment indicator which takes the value 1 if households participate in non-farm work and 0 otherwise. One critical challenge in estimating the ATT is unobserved counterfactual situations. Thus, it is virtually impossible to observe the potential outcomes of farmers who participated in non-farm work had they not participated. Replacing this unobserved counterfactual with the potential outcomes of farm households who have not participated in non-farm activities is also not viable, as it is likely to result in bias estimates (Takahashi and Barret, 2013). We address this challenge using our primary model, endogenous Poisson treatment effect as described by Terza (1998) and the IPWRA estimator proposed by (Wooldridge, 2007). IPWRA provides a viable solution when biased estimates (ATT) arise from propensity score models when misspecification occurs (Wooldridge 2007). This ensures that the IPWRA results are consistent since their double-robust property makes it possible to determine the treatment and the outcome models.[1]

2.1.1. Endogenous treatment effect model for a count outcome – Poisson

As shown above, we are interested in whether active involvement in non-farm employment has a causal effect on the intensity of adaptation strategies adopted by farming households. There is no doubt that participating in non-farm work is not exogenous. Thus, non-farm work is considered as an endogenous binary-treatment variable T_j. T_j is endogenous if treatment assignment is not random, but some unobservable covariates (variables) are affectingT_j that also affect the outcome variable Y_j. Since the adoption of climate change adaptation strategies (outcome variable) is a count event taking the values, $Y_j = 0, 1, 2, \ldots\ldots Y_n$ and farm households decide whether to adopt a number of them or none, we define a second dummy S_j that represents a sample selection rule. That is participants of farming households may not adopt any of the many adaptation strategies. In this case, the $S_j$is missing for a proportion of the sample and the selection rule is defined such that $S_j = 1$ when Y_j is observed and $S_j = 0$ when Y_j is missing. Following Miranda (2004), we address the issue of endogeneity and sample selection using the count data model with endogenous treatment.[2,3,4] The Poisson endogenous treatment effect model considers the case where selection dummy S_j is assigned the value 0 when a farm household adopt none of the climate change adaptation strategies (Y_j is missing) and 1 when farm household adopt a number of the climate change adaptation strategies (Y_j is observed). The endogenous treatment and the selection dummies can be generated according to the continuous latent variables as;

$$T_j^* = Z_i' \gamma + \mu_j \tag{2}$$

$$S_j^* = X_j' \beta + \delta T_j + \varepsilon_j \tag{3}$$

with $T_j = 1(T_j^* > 0)$, $S_j = 1(S_j^* > 0)$. The outcome model which follows a Poisson distribution can be specified as;

$$Y_j = \begin{Bmatrix} 0 & if\ S = 0 \\ [\mu^{Y_j} \exp(-\mu)] / Y_j! & if\ S = 1 \end{Bmatrix} \tag{4}$$

$$\text{Thus, } E(Y_j / X_j, T_j, \varepsilon_j) = \exp(X_j \beta + \delta T_j + \varepsilon_j) \tag{5}$$

X_j denotes the vector of covariates use to model the count outcome, z_j are the covariates for binary treatment, and the ε_j and μ_j are the error terms for the outcome and the treatment, respectively. The two error terms are bivariate normal with mean zero.

The covariates X_j and z_j are exogenous, thus, they are not related to the error terms. Conditional on ε_j, μ_j is normal with mean $\varepsilon_j \rho / \sigma$ and variance $(1 - \rho^2)$. In estimating the ATE and ATT, the endogenous-treatment Poisson regression model is nested in a potential outcome model. The potential outcome model specifies what each individual farm household would obtain in each treatment level.

2.2. The study area, sampling techniques and data source

The study was conducted in the south-western Nigeria, which consists of Lagos, Ogun, Oyo, Osun, Ondo and Ekiti states. South-western Nigeria has a tropical climate with rainy and dry seasons. The temperature varies between 25 and 35 degrees Celsius, and the annual rainfall ranges between 1300 and 2500 mm. The wet season is associated with the Atlantic Ocean's Southwest monsoon wind, while the dry season is associated with the Sahara Desert's Northeast trade wind. The ecological conditions in South-western Nigeria are mangrove and the land where the belt of swamp vegetation blends into secondary forest occurs, from the Ogun and parts of Ondo states to the inland where some plants grow. Cassava, yam, millet, rice, plantains, cocoa, palm, cashew, and maize are among the crops that thrive in this environment.

The participants for the survey were chosen by means of a multi-stage sampling method. The first phase was a typical case selection in the same agro-ecological region of three states (Ekiti, Ondo and Osun). The selection of the states was based on production intensity of rice in the areas. In the second phase of the selection process, two Local Government Areas

[1] The mathematical equations used in estimating IPWRA can be found in Imbens and Wooldridge (2009). Readers are encouraged to consult this article to enhance their understanding.

[2] The endogenous–treatment Poisson regression model in this study was fitted by Stata command ‘etpoisson’ using maximum likelihood estimator as described by Terza (1998). Terza (1998) categorized the model fit by etpoisson as endogenous-switching model, that involves a binary switch that is endogenous for the outcome such as ours. The model fit by the etpoisson command allows ATE and ATT to be estimated.

[3] The estimation of endogenous count model uses FIML and it is fitted by the Stata command espoisson. Miranda (2004) describes the endogenous switching model for count models.

[4] There are a number of count data models such as Poisson, negative binomial, zero inflation Poisson, zero inflation negative binomial, and truncated Poisson. However, our preliminary analysis indicates that Poisson regression model better fits our data. Hence, Endogenous Poisson treatment effect model was used.

(LGAs) from each of the selected states were purposively sampled based on the density of smallholder rice farmers in the region. In the third stage, from each of the six LGAs, five rural communities were randomly selected. In this context, 12 rice-farming households were chosen from each of the five villages, for a total of 360 rice-farming households as the sample size for this analysis. The primary data, which was cross-sectional, was collected using a well-structured questionnaire. It worth noting that the questionnaire for this study was approved by the Humanities and Social Science Research Ethics Committee of the University of KwaZulu-Natal, Pietermaritzburg, South Africa, with Protocol Reference Number: HSS/0319/017D. In addition, verbal consent was obtained from each respondent, and confidentiality was maintained by assigning codes for each respondent instead of recording their names.

3. Results and discussion

3.1. Descriptive analysis of the results

The description of the dependent and the explanatory variables in the model estimates is reported in this section. The data reveals that 196 (representing 54.44%) of the farm households were participants of non-farm work, while 164 (representing 45.56%) had not participated in any non-farm economic activity. Section 3.1.1 discusses the descriptive statistics of the independent variables included in the models. The adoption of adaptation strategies as dependent variables is detailed in section 3.1.2.

3.1.1. Description of independent variables

The descriptive statistics of the explanatory variables are listed in Table 1. It was hypothesized that these explanatory variables could influence non-farm participation and adaptation strategies used by the farmers. From the 360 responses, a little more than half were males and the average age of the farmers was 47 years, which suggests that the majority of our farmers were in the productive age bracket. At least the primary level of education was achieved by the majority (about 62%) of respondents. The average household size was about five members, and farmers had, on average, 16 years of experience in crop farming. About 54% had engaged in at least one non-farm economic activity, and the average farm size allocated to rice production was about three hectares. As in many developing countries, about 50%, 55%, and 64% of the farmers in our sample suffered from access to extension services, were credit constraint, and had not accessed information on climate change, respectively. These variables are key to adopting the strategies of climate change adaptation. Therefore, farming households must have access to information on climate change and understand how adaptation strategies can minimize the negative consequences before they are able to consider adaptation strategies on their farms (Deressah et al., 2011; Pandeya et al., 2018).

Moreover, about 42% and 37% of the sampled farmers experienced flood and drought, respectively in the last five years while about 78% believed that climate change exists in their locality. About 60% had the opportunity to visit rice demonstration farms, while about 54% of the farmers were members of farmer groups. Moreover, 37.5%, 23.9%, and 38.6% of the respondents were drawn from Ekiti, Osun, and Ondo state, respectively.

3.1.2. Adoption of adaptation strategies to climate change – dependent variables

For centuries, farming households have been employing actions before the impact (ex-ante response) in response to risks and shocks of climatic change, and these adaptation strategies are considered as usual (Abid et al., 2020). For example, farmers usually adopt strategies such as fertilizer application, application of insecticides, crop diversification,

Table 1. Definition and summary statistics of the explanatory variables used in the analysis.

Variables	Description of variables	Mean	SD
Socioeconomic characteristics			
Gender	1 = if respondent is male, 0 otherwise	0.558	
Age	Age of the respondent in years	47.283	7.671
No education	1 = if respondent had no formal education	0.375	
Primary education	1 = if respondent had primary education	0.347	
Secondary education	1 = if respondent had secondary education	0.142	
Tertiary education	1 = if respondent had tertiary education, 0 otherwise	0.136	
Active family labour	Number of family members working in the farm	4.658	1.243
Crop farming experience	Number of years in crop farming	15.733	5.088
Household asset			
Participation in Non-farm work*	1 = if respondent engaged in non-farm employment	0.544	
Farm size	Number of hectares allocated to rice farming	2.981	1.232
Institutional/policy variables			
Access to extension services	1 = if respondent had access to extension in the last 24 months	0.511	
Visit to demonstration farms	1 = if respondent had visited rice demonstration farms	0.586	
Credit access	1 = had accessed agricultural credit	0.450	
Membership of FBOs	1 = if respondent is members of FBO, 0 otherwise	0.542	
Market distance	Distance from house to market (km)	14.445	12.592
Climate variables			
Access to information	1 = if respondents had received information on climate change, 0 otherwise	0.364	
Flood	1 = if respondent's household was affected by flood during the last five years, 0 otherwise	0.420	
Drought	1 = if respondent's households was affected by drought during the last five years, 0 otherwise	0.370	
Climate belief	1 = if the respondent belief climate has change in the local area	0.786	
Location variables			
Ekiti state	1 = if respondent is located in Ikiti state	0.375	
Osun state	1 = if respondent is located in Osun state	0.239	
Ondo state	1 = if responded is located in Ogun state	0.386	

Note: SD denotes standard deviations. *Participation in non-farm employment is the endogenous treatment variable in the endogenous Poisson regression model. FBOs denote Farmer-based Organizations.

income diversification, among others. Farmers most often plan strategically according to their needs and capabilities; therefore, climate change adaptation strategies vary from household to household. There were many adaptation strategies employed by farmers in the study area. However, all the adaptation strategies were condensed into 11 conventional approaches used by smallholder rice farming households and, these are listed in Table 2.

During the time of the survey, a value of 1 was assigned to each climate change strategy adopted and 0 otherwise. From Table 2, there is marginal disparity observed between participants and non-participants of non-farm work; hence, the pooled sampled values are used in the discussions.

The most widely practiced agricultural related adaptation strategy employ in the study area was changing farming calendar with about 70% of the farmers engaging in that practice as a form of adaptation strategy. Farmers noted that natural changes in climatic variables such as rainfall and temperature patterns can cause changes in planting and harvesting dates, and they often observed these changes by consulting meteorological agencies, as well as the use of their long-standing experiences. Since planned measures such as irrigation systems and other non-farm livelihood strategies are not well developed, farmers quickly change their farming calendar to coincide with the variability of the climatic parameters (Asfaw et al., 2018). A similar result was documented by Asfaw et al. (2018) in Ethiopia where changing of planting date was identified as one of the key adaptation strategies to climate change.

Diversification of crop types and varieties (including crop substitution) is another dominant strategy used by farmers in response to environmental variations and economic risks associated with climate change. Farmers usually engage in multiple cropping systems to serve as insurance against single crop failure or intercrop with legumes such as cowpea and soybean as a way of fixing nitrogen to increase productivity or as cover crops to minimize heat stress that may be experienced by the plants. Livestock diversification is another strategy used by the farming households to address the economic risks associated with climate change. The composition of animals ranges from cattle to small ruminants such as sheep and goats, and poultry such as chicken, turkey, and ducks. About 66% and 60% of the respondents used crop and livestock diversification, respectively, as some of their strategies to respond to climate change. Sharecropping is a system of crop production in which landowners lends out their land to tenants in return for a share of the crops produced on that land (Mukhamedova and Pomfret, 2019). Thus, to reduce the risk of climate-related productivity or income loss, farmers invest in share-cropping and futures (Mukhamedova and Pomfret, 2019).

Another climate change mitigation practice that is common among rural farming households is the long-term storage of crops or seeds. Cereals, particularly rice and maize are usually stored to be sold later when money is needed or in the event of current season's crop failure. Seeds are also stored as a reserve when seeds are scarce or when seeds are destroyed. Seedbank as an adaptation strategy provides farmers with seeds reserve, minimize the incidence of hunger and food insecurity, and insurance against catastrophic event or drought. Past experiences make farmers concerned that climate change can cause extreme weather conditions, which may lead to a disturbance of the biodiversity. Hence, one of the principal reasons of seedbank is to protect seeds and conserve the biodiversity of the crops. Another significance of seedbank is to have enough seeds to sell or in exchange for other inputs when there is an emergency resulting from a change in climatic conditions. Crop specialization is another strategy employed by farmers to combat the damaging impacts of climate change. When farmers receive information or perceive long term drought, they tend to specialize in a more drought-tolerant crop such as millet, sorghum, cowpea and sometimes cassava to overcome the failure of rains and its negative impact on productivity. Moreover, farmers tend to reduce their land size being cultivated as a way of guiding against the risk of long-term drought when they perceive it.

Regarding technology-related adaptation strategies, use of improved crop variety (both hybrids and open-pollinated) whose traits have been improved for characteristics such as pests and disease resistance, drought-tolerance, salinity stress resistance, early maturing, high-yielding and quality enhancement dominate among those strategies. Seeds with these traits are essential to farmers due to erratic rainfall and high temperatures. A similar finding was identified by Taruvinga et al. (2016) in South Africa where rainfall-dependent farmers use improved varieties to avert productivity loss. Weather extremes such as erratic rainfall and high temperatures introduce some pests and diseases into the environment that affects plant growth. Application of agrochemicals such as insecticides, and herbicides have been used as protective strategies to fight against pests and diseases. Thus, farmers may apply pesticides because they may receive information or perceive a change in weather conditions (Le Dang et al., 2014; Adem et al., 2014).

A study by Biesbroek et al. (2013) revealed that excessive drought contributes to soil infertility and poor soil retention. Farmers in the study area also believe that high temperatures usually make the soil dry and kill the pathogens in the soil. They, therefore, practice mulching or composting to improve the soil moisture content. It is, therefore, not surprising that organic fertilization of the soil using manure or mulching is also practiced by about 59% of the respondents. Soil and water

Table 2. Major adaptation strategies to climate change practiced by farm households.

	Pooled	*Participants*	*Non-participants*
Adaptation strategies	Mean	Mean	Mean
No adaptation strategies	0.197	0.168	0.232
Agricultural related adaptation strategies			
Varying of land size (VLS)	0.464	0.418	0.518
Changing farming calendar (CFC)	0.697	0.724	0.665
Sales of crops/seedbank (SC_S)	0.578	0.571	0.585
Sharecropping (SC)	0.594	0.607	0.579
Livestock diversification (LD)	0.597	0.597	0.598
Crop diversification/multiple/intercropping (CD)	0.661	0.688	0.628
Crop specialization (mono-cropping) (CS_M)	0.536	0.555	0.521
Technology application related adaptation strategy			
Use of improved crop variety (ICV)	0.703	0.735	0.665
Application of Agrochemicals (AG_CH)	0.678	0.694	0.659
Application of organic fertilizer/mulching (ORG_FZ)	0.594	0.571	0.622
Application of soil and water conservation (SWC) practices	0.672	0.694	0.646

Note: c denotes significance level at 10%. Participants refer to farm households who participated in non-farm work while non-participants denote those who did not.

conservation practices such as terracing on the slope, planting trees along the contour, watershed management, irrigation, and water harvesting are made use of in the study areas to overcome the negative impacts of climate change. The finding is not unexpected, because 67% of farm households in the study area practice SWC technique to cope with climate change. Recent studies such as Asfaw et al., (2018), Ojo and Baiyegunhi (2020), and Adeagbo et al. (2021) have also identified similar strategies used by farmers to mitigate against the negative effects of climate change.

The extent to which farmers adopt climate change adaptation strategies are reported in Table 3. Some households take no action concerning climate change, while others attempt to adapt to changing climate conditions. More than 80% of the respondents have taken action to mitigate the effects of climate change (Table 3). Overall, about 28% of the farming households practiced all of the adaptation strategies considered in the survey.

3.2. Empirical results and discussions

The output from the Poisson endogenous treatment effect model is presented in Table 4. The *Wald Chi*^{2} (*32.46, p* $>$ *0.009*) indicates that the model is statistically significant at 1%, which suggests a good fit. The *Wald* independence test value ($\rho = 0$*) (37.07; p* $>$ *0.000*) indicates the denial of the null hypothesis of no correlation between the error term of non-farm employment participation and the error term of the number of adaptation strategies adopted. The significance of the *rho* (ρ) implies that unobserved characteristics of the farming households that influence their participation decisions in non-farm work also affect climate change adaptation strategies. The use of the Poisson endogenous treatment effect model to address the problem of endogeneity is therefore in order. The determinants of participation in non-farm income (probit regression results) is reported in column 2 and 3, while the number of adaptation strategies (the Poisson regression results) are presented in column 4 and 5 of Table 4. The two output are discussed further in subsection 3.2.1 and 3.2.2.

3.2.1. Determinants of non-farm work participation

Starting with the determinants of nonfarm jobs, socioeconomic variables such as gender, respondent age, educational attainment, and crop farming experience all have a major impact on nonfarm employment participation.

The findings showed that female-headed households are more likely than male-headed households to diversify into non-farm economic activities. This could be attributed to the general situation in Nigerian rural communities, where women lack access to productive resources, especially farmland. Women who have access to land are more likely to have gotten it from their husbands, so they are more likely to pursue non-farm sources of income. Our findings corroborated the findings of Awotide et al. (2017), who found that female-headed households in Nigerian farming communities participate in more economic activities than male-headed households.

The age of the respondent is significant in predicting nonfarm behavior, negatively signed, suggesting younger farmers were more likely to diversify their income into different areas of the economy. The reasonable explanation for this is that old age has a negative correlation with physical strength. As a result, as the household head ages, they are expected to rely more on farm income and less on their non-farm income. Similar to works of Sallawu et al. (2016) and Awoniyi and Salman (2012), the age of farmers negatively affects the likelihood of them actively engaging in non-farm activities. As indicated in Table 4, household heads with relatively high educational attainment were more likely to engage in non-farm work, as revealed by the positive and significant estimate of the secondary education variable. This is not surprising as education is a powerful human capital that makes people aware of the series of opportunities for generating income. This finding is in line with the result of a similar study in Northern Ghana by Issahaku and Abdul-Rahaman (2019) and Asravor (2018). Similarly, the number of years of crop farming reduces the likelihood of participation in non-farm economic activities, as shown by the negative and significant estimate. Likewise, the size of the rice farm is positively correlated with participation in non-farm work. Thus, farmers with larger farm sizes under rice cultivation have higher propensity to participate in non-farm economic activities. Moreover, income from rice farm correlate negatively with participation in non-farm work. This could be ascribed to the fact that farmers who get higher income from their farms tend to concentrate on the farm business, thereby participating less in other non-farm economic activities.

Extant of empirical evidence (e.g., Das 2017; Dagunga et al., 2018) have established a significant and positive correlation between institutional or policy variables and participation in non-farm work. Similar to these previous studies, farmers' contact with agricultural extension agents have a significant and positive relationship with participation in non-farm employment. This is in line with the modern way of delivering extension services where farmers are not only giving information on agricultural innovation, but how they can also spread their risk through engagement in multiple sources of income, especially in non-farm work. The study further revealed that social network variables such as membership of FBOs increase the probability of farmers' participation in non-farm work. This is not surprising as some NGOs operating in rural communities in Nigeria train farmer-groups on alternative livelihood programmes such as soap-making, textiles, and other micro-enterprise. Access to climate change information had a positive and significant impact on participation in non-farm employment. This result suggests

Table 3. Intensity of climate change adaptation strategies by participation in non-farm work.

Adaptation Strategies	*Pooled sample*		*Participants*		*Non-participants*	
	Freq.	%	Freq.	%	Freq.	%
0	71	19.72	33	16.84	38	23.17
1	18	5	10	5.1	8	4.88
2	8	2.22	5	2.55	3	1.83
3	16	4.44	11	5.61	5	3.05
4	10	2.78	6	3.06	4	5.61
5	10	2.78	8	4.08	2	1.22
6	5	1.39	4	2.04	1	0.61
7	13	3.61	7	3.57	6	3.66
8	11	3.06	8	4.08	3	1.83
9	22	6.11	14	8.54	8	4.08
10	76	21.11	45	22.96	31	18.9
11	100	27.78	51	26.02	49	29.88

Table 4. Determinants of Non-farm participation and adoption of climate change adaptation strategies.

Variables	*Non-farm employment*		*Adaptation strategies*	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Socioeconomic characteristics				
Gender	-1.80864***	0.2308	-0.0379	0.0234
Age of respondent	0.1013*	0.0565	0.0007	0.0012
No education	-0.3207	0.7377	-0.0181	0.0305
Primary education	0.3161	0.3625	0.0073	0.0138
Secondary education	0.3978***	0.0286	0.0732***	0.0013
Household size	-0.4593	0.3411	-0.0082***	0.0020
Crop farming experience	-0.4707***	0.1409	-0.0031	0.0036
Household asset				
Participation in Non-farm employment			0.1011**	0.0474
Farm size	0.4006**	0.1847	0.0089*	0.0049
Market variables				
Farm revenue	-1.5789**	0.5549	0.1482***	0.0214
Distance to market	0.599	0.615	0.530	0.338
Institutional/social network variables				
Access to extension services	0.6547***	0.0455	0.0354**	0.0171
Visit to demonstration farms	0.8019	0.9821	0.0123	0.0186
access to agric. Credit	0.7943	0.8374	-0.0378	0.0239
Membership of FBOs	1.7793***	0.6988	0.1118***	0.0404
Climate variables				
Access to information	1.0439**	0.4947	0.0168***	0.0021
Flood	0.106	0.172	0.256***	0.078
Drought	0.307	0.266	0.313***	0.042
Climate change belief	0.003	0.002	0.961***	0.128
location variables				
Ekiti state	-1.9504**	0.7276	0.0031	0.0192
Osun state	-5.3533***	1.0829	-0.1189***	0.0376
Constant	16.7042**	7.5525	1.3017	0.2857
Wald Chi^2 (17)	31.79	0.016		
Rho (ρ)	0.9976	0.0007		
Sigma (σ)	1.9573	0.12002		
Wald test of ind. equations ($\rho = 0$)	45.46***	0.000		

***, ** and * denote significance levels at 1%, 5% and 10%, respectively. Ondo state was used as a base category for location variables while tertiary education was used as base category for educational variables.

that increasing farmers' understanding of the negative effects of climate change makes them better able to withstand those effects. Shongwe et al. (2009) and Asfaw et al. (2016) reported similar findings in East Ethiopia and North Central Ethiopia, respectively. Finally, farmers in Ekiti and Osun states are less likely to engage in non-farm work than their counterparts in Ondo state (base category).

3.2.2. *Intensity of climate change adaptation strategies*

From Table 4, two variables in the socio-economic characteristics category have a significant influence on the intensity of climate change adaptation strategies. The secondary education coefficient is positive and has a significant influence on the likelihood of adopting more climate change adaptation strategies. The findings are consistent with previous studies by Asfaw et al. (2018). A household size decreases the probability of implementing more adaptation strategies, as indicated by a negative and significant estimate of the house size variable. This may be because households with more members need higher expenditures to meet their family's needs; as a result, they have less liquid resources to invest in adaptation strategies. However, because of the availability of family labor, these households may as well prefer to rely on labor-intensive techniques to increase productivity. The results are consistent with those reported by Taruvinga et al. (2016). However, studies such as Ali and Erenstein (2017) and Adeagbo et al. (2021) reported a positive relationship between climate change adaptation strategies and household size citing available of family labour as the most probable explanation.

The positive and significant relationships between farm size and adaptation strategies suggest that households with larger lands dedicated to rice cultivation are more likely to employ a variety of adaptation strategies. Similarly, high income from rice farm encourages farmers to adopt more of the climate change adaptation techniques. This could be that high farm incomes enable farmers to invest in their farms for a high expected returns through adoption of some of the climate change adaptation techniques. In addition, participation in non-farm economic activities has a positive and significant effect on the adoption of climate change strategies.[5] This result uphold the findings of Deressa et al. (2009).

The results further attest to the fact that supply-side policies (e.g., extension services, membership of FBOs) have a positive effect on farmers' propensity to adopt a number of adaptation strategies. Thus, extension services, membership of FBOs, and access to climate change information significantly affect intensity of adaptation. By providing farmers with information that can be used to predict the variations in weather parameters help them to effectively use climate change

[5] The detailed discussion of participation in non-farm employment variable is reserved for next section.

Table 5. Treatment effects for the number of climate change adaptation strategies' adoption.

Treatment effects	Coefficient	S.E
Poisson regression with treatment effects		
Average treatment (ATE)	9.399**	5.235
Average treatment effect on the treated (ATT)	8.697**	4,766
Inverse Probability Weighted Regression Adjustment (IPWRA)		
Average treatment effect (ATE)	7.103***	0.276
Average treatment effect on the treated (ATT)	7.245***	0.289

Note: The bootstrap replications were changed from 100 – 1,000 but no significant change occurred, hence 500 replications were used to bootstrap the standard errors in the IPWRA analysis.

adaptation strategies (Mihiretu et al., 2019; Omerkhil et al., 2020; Zakaria et al., 2020). Furthermore, farming households that experienced floods and droughts in the last five years employed a wide range of adaptation techniques on their farms to mitigate the effects on their livelihoods. The findings are consistent with that of Khanal et al. (2018), who found significant positive relationships between drought occurrence and adaptive climate change strategies.

3.3. *Estimated impact of non-farm work on climate change adaptation strategies*

The primary focus of our study is to examine the impact of participating in non-farm employment on farmers' adoption of climate change adaptation strategies. The descriptive statistics was used to compare the mean adaptation strategies that are adopted by both non-farm employment participants and non-farm employment non-participants. The findings from the study showed that the average number of climate adaptation techniques employed by participants in non-farm work is higher than the average number of such techniques used by farmers who were not engaged in non-farm work. A simple considerable difference in the average number of adaptation strategies between participants and non-participants of non-farm work in impact evaluation studies is misleading as they usually fail to control for potential differences in the characteristics between the two groups. The estimate from the endogenous Poisson regression model can also be inadequate though it accounts for endogeneity. This is because direct coefficients from the model cannot be considered as ATT since the issue of missing data (counterfactual scenario) has not been accounted for.

We, therefore, turned to the results of the effects of the participating in non-farm work on farmers' adaptation strategies using ATE and ATT, where the Poisson regression with endogenous treatment effects was used and then complemented with IPWRA as a robustness check. The ATE and ATT were estimated after fitting the Poisson regression with endogenous treatment effects.[6] As indicated in Table 5, the estimated potential outcome means (ATE) of participation in non-farm work on intensity of adaptation is about 9.4 and it is statistically significant at 1 %. The ATE estimate suggests that the average farming household who participate in non-farm in the entire sampled population used about nine (9) additional strategies to minimize the impacts of climate change. Similarly, the conditional treatment effect which measures the ATT of participation in non-farm work on intensity of adaptation is about 8.7 and also statistically significant at 1%. Thus, a farming household who engaged in non-farm work applied an average of about 8.7 more of climate change adaptation strategies than it would if it did not participate in non-farm work.

Consistent with the Poisson endogenous treatment effects, IPWRA produces significant gains in the number of adaptation strategies resulting from participation in non-farm work. Thus, participants of non-farm work adopted 7.23 more than they would have adopted if they did not participate in non-farm work.

The results of the two analytical methods show that the number of strategies that farmers used to curtail the negative impacts of climate change was greatly increased by participation in non-farm work. Studies conducted by Sallawu et al. (2016) and Deressa et al. (2009) in Nigeria and Ethiopia share the positive impact of non-farm work on climate change adaptation strategies. Similarly, Kassie et al. (2015) and Adeagbo et al. (2021) reported that participation in non-farm economic activities provided farmers with sufficient financial flexibility to adopt a number of climate change adaptation strategies. Our finding revealed that taking part in non-farm businesses will provide farming households with needed capital and reduce their overall need for credit facilities, thereby promoting their investments in agricultural productivity inputs, as well as other adaptation strategies to reduce risk of production.

4. Conclusion and policy implications

This study links non-farm employment and climate change adaptation strategies, estimating the impact of non-farm employment on climate change adaptation intensity. Poisson regression with endogenous treatment effect model was employed where factors influencing both endogenous variable (non-farm work) and intensity of climate change adaptation techniques were identified through simultaneous estimation. In terms of adopting climate change adaptation strategies, the key factors influencing the intensity of adaptation are the achievement of secondary education, household size, farm size, extension services, membership of FBOs and access to information on climate change.

After controlling for observed and unobserved covariates, results indicate that participation in non-farm economic activities increases farmers' adaptive capacity by adopting more strategies than they would have in the absence of non-farm employment. Therefore, it is important for smallholders to enhance their adaptive capacity by using a variety of adaptation approaches. Agricultural policy efforts should focus on non-agricultural opportunities to help farmers transition to alternative forms of employment, particularly during off-season periods. Non-farm employment strategies could be incorporated into existing programs like extension service delivery. These programs should be well-designed to enable farmers to use appropriate farm management practices while also educating them how to safeguard their farms from the adverse effects of climate change through non-agricultural occupations. Non-farm jobs can thus become an increasingly important aspect of a farming household's diversification strategy, as it offers opportunities to reduce the risk of climate change and create resilience, which will improve land productivity. Furthermore, the study suggests non-farm livelihood programs that would engage the rural labor force, particularly during the off-season. Nonfarm employment income could be reinvested in farm operations and other climate change mitigation strategies. Finally, the study suggests that more research into the economic and environmental risks

[6] ATE and ATT were estimated as a post-estimation after fitting the Stata command etpoisson for Poisson regression with endogenous treatment. The ATE estimated after etpoisson is the potential outcome means while ATT is the conditional treatment effect.

associated with some climate change mitigation strategies, as well as their long-term viability in developing countries, is critical.

Declarations

Author contribution statement

Gideon Danso-Abbeam: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Temitope O Ojo, Lloyd J.S Baiyegunhi & Abiodun A. Ogundeji: Analyzed and interpreted the data; Wrote the paper.

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Data will be made available on request.

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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