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Driver Factors of Climate Change Household Perception in Southwest, Nigeria: An Application of Interaction Probit Model

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Abstract: Policymakers in many developing countries have been preoccupied with the task of ending hunger, achieving food security and improved nutrition and promote sustainable agriculture as one of the Sustainable Development Goals (SDGs). This paper examine the drivers' factors that influence the perception of climate change in southwest Nigeria. A well structural questionnaire was used to obtain information from 180 farming households in the study area. Descriptive statistics and interaction probit regression were employed for data analyses. Result showed that (89.9%) of the male respondents perceived the change in climate while about 70% of the female respondents perceived that there is change in climate. Also all educated farming household perceived a change in climate. The binary response of climate change perception is regressed on a range of variables including age, gender, years of education, farmer experience, farm size, income, access to credit, contact with extension agent, access to climate information, increases in temperature, incidence of flood, pest and drought produced good fits as revealed by statistical significance ($p<0.01$) of the likelihood ratio chi square. This show the need to integrate interactions among household variables in activity-based predicting models. It was concluded that efforts at increasing awareness and perception of climate change by promoting education of farming households will go a long way in increasing the awareness and perception of the climate change in the study area.

Keywords: Climate change, perception, interaction probit, interaction effect, southwest, Nigeria

1. Introduction

Climate change is one of the most serious challenges facing man's existence in the twenty-first century. The conscious understanding or perception of climate change is a topic that is greatly important for climate scientists, as well as individual, group, government and international organization, because it is a key to develop an appropriate strategic decision relating to adaptation and mitigation of the challenges of climate change (Adger et al., 2003). Studies of public perception of climate change is very prominent in United State of America, though the American public have moderate risk perception of climate change (Dunlap $ Saad, 2001; Leiserowitz, 2006), because American did not see themselves personally at risk. Their perception of dangers to climate change are to geographically distant people, place and non-human. However, most studies on climate change in the developing countries have narrowed their attention to climate change impacts, adaptation and risk assessment on agricultural crops and livestock (Rosenzweig and Parry, 1994; Hassan 2010; Maddison, 2007). Whereas it is now therefore established that the devastating effects that resulted from the changes and variations in climate system cannot be viewed in isolation from those of the human systems since it is biophysical and socioeconomic in nature. However, major theories of choice under risk or uncertainty are cognitive and consequentialist (Loewenstein et al., 2001; Leiserowitz, 2006). These theories attempted to model how people make rational and analytical choice but failed to account for affect (people feelings about specific idea) and emotions because it is believe that people feeling is short phenomena, and easily went away with the event occurrence (Leiserowitz, 2006). Unfortunately, Affect and emotion are not just short term, but often arise prior to cognition and play an important role in subsequent rational thought (Lowenstein et al., 2001). Leiserowitz, (2006) opined that climate change perception can fundamentally compel or constrain political, economic and social action to address particular risk. Improved perception of climate change by rural households will improve their awareness of the adverse effect of climate change, such as increase in temperature and low rainfall. Studies on climate change perception (Tesfahunegn, 2016; Ayanlade, et al., 2016; Gbetibouo, 2009; Maddison, 2007; Leiserowitz, 2006) revealed that majority of the rural populations are already aware of the change in climate. Ayanlade et al., 2016 compared smallholder farmers' perception of climate change with metrological data in southwest Nigeria, the finding revealed that perception of rural farmers on climate change and variability are consistent with the climatic trend analysis. However, despite the significance of the knowledge of climate change by rural households, driver factors that determine rural household perception of climate change and the interaction of the key indictors in southwest, Nigeria and many developing countries are scanty. The fact that climate has changed in the past and will continue to change in the future underscore the need to understand the way farmers perceive it. Such information is crucial as it will help to guide against the future occurrence.

Gbetibouo, (2009) reported that climate change perception are influenced by different household and farm characteristics, institutional factors), and the exposure to effect of climate change events (Leiserowitz, 2006). Collectively, household characteristics believed to have affect the perception of climate change are: age, educational level and the gender of household head, family size, wealth, and years of farming experience. Maddison (2006) asserted that farming experience which is most often associated with age, is a key factor in the climate change perception. He also indicated that experienced farmers are more likely to perceive climate change better than the less experienced ones. Experiences of the previous occurrence of climate change overtime would have made the experienced farmer to have a better knowledge and information on changes in climate change condition. The level of education of the household head has also been hypothesized to be positively related to the perception of climate change. Gender of the household is also hypothesized to influence the perception of climate change. Although several studied have showed that social factors had allowed male headed household to handle agricultural activities issues which may improve their perception on climate change through trial and errors over long time (Tesfahunegn et al., 2016), but Nhemachena and Hassan (2007) had showed a contrast result, they find out that female headed households in southern Africa are more likely to take to perceive change climate because most rural smallholder farming in the region are carried out by women. Hence, women are more exposure to the effect of climate change. Family size influenced on climate change perception is unclear, as large family size can share climate related information and thus affect positively perception on climate change. However, Shiferaw and Holden, (1998) claimed that there is possibility that a large family size might be force to depend on daily labour work (off-farm) in an attempt to earn income to ease the consumption pressure imposed as a result of large family size, which results in poor perception on climate change. Family size thus influences positively and negatively farmers perception on climate change (Shiferaw & Holden, 1998)

Institutional factors often considered in the literature to affect the perception of climate change are access to information via extension agent or/and other sources such as mass media (Leisrowitz, 2006). Moreover, climate change indices which include extreme weather events exhibited in variability in timing and intensity of rainfall, incidence of flood, drought and higher temperatures have also been identified as factors driving climate change perception by rural households.

Mounting scientific evidence suggest that seasonal-mean temperature anomalies have changed dramatically in the past three decades (Hansen, et al, 2012). This distributional changes of seasonal mean temperature anomalies has shifted toward higher temperatures and the range of inconsistencies has increased. Rainy season in the southwest Nigeria which usually start in March every year has now shifted to April or sometime end of May of every year or in some years. Despite this starring climate change induced inhibiting reality, more than 95% of agricultural production in sub- African is rain-fed (Adebisi-Adelani & Oyesola, 2014).

Several studies on climate change have reported the impacts of climate change on agriculture and natural resources management in countries of Africa (Winters et al., 1998; Kurukulasuriya et al., 2006; Hassan & Nhemachena, 2008; Speranza, 2010). Therefore, rural households whose major means of livelihood is rain-fed agriculture in Sub-Saharan Africa are mostly prone to the effect of climate change (Agbo, 2013; Van Wesenbeeck et al., 2016). Reason for this ugly trend is not far-fetched it is as a result of poor infrastructural and technological development, prevalence of poverty and high dependence on rain-fed agriculture (Ayanlade et al., 2016; Lipper et al., 2014; Nelson et al., 2014; Adimassu & Kessler, 2016). Agwo et al., (2011) and World Bank, (2007) claimed that climate change also limit agricultural production due to unexpected heavy rainfall or a prolonged extreme frequent droughts. It thus become important to ascertain rural households' perception of climate change, their determining factors and the variations in their beliefs about climate change,

The study will also consider the interaction and effects of key variables that influence the probability of climate change perception. Variable interactions an area that have not been explored in literature on rural households climate change perceptions. Why this assertion is? This becomes important to further empirically establish that factors casually projected as causes for observed variation in rural households' perceptions to climate change are indeed those responsible for the variations.

2.0 Material and Methods

2.1 Study Area

The research work was carried out in South-West geo-political region of Nigeria. The South-West part of Nigeria is the home of the Yoruba tribe consisting of six states: Ekiti, Lagos, Ondo, Osun, Oyo and Ogun. It lies within latitude 4^0 -14^0 N and latitude 3^0 - 14^0 E and exhibits the typical climate of averagely high temperature and high relative humidity. There are two distinct seasons, namely the rainy season, which lasts from March/April to October/November, and the dry season, which lasts for the year to October/November till march/April. The temperature is relatively high during dry season with the mean around 33^0C. The harmattan brought in by hot, dry, northeast trade wind from December- February, has ameliorating effects on the dry season high temperatures. Low temperatures are experienced during the rains, especially between July and August when the temperatures could be as low as 24^0C. The distribution of rainfall varies from about 100mm to about 2000mm.

The south western part of Nigeria has three main types of vegetation, namely, mangrove forest, tropical rain forest and guinea savanna. Southwest Nigeria covers about 114,271kilometer square land area, approximately12 percent of Nigeria total land mass. The total population is 27,581992 and predominantly agrarian. Major food crops grown in the area include cassava, cowpea, and yam (NPC, 2006).

2.2 Sampling procedure and sample size

A three stage sampling procedure was used in collecting data for the study as shown, in the first stage; two state namely Oyo and Ekiti was randomly selected out of the six states in the southwest region. In the second stage, proportionate sampling technique was employed to select Local Government Area (LGA) from the states, three (LGAs) was selected from sixteen LGAs from Ekiti State, while six LGAs were selected from the thirty three LGAs from Oyo state. This is because the states did not have equal numbers of Local Government Area. At third stage, two towns were randomly selected from each of the Local Government Area, using delineation of states into villages and towns in 2006 by the National Population Commission (NPC) was adopted for the study. A list based on the enumeration Areas (EA) used for 2006 census purposes by the National Population Commission for households in the study area was obtained from the commission. This list serves as the sample frame for each block. A list of 180 households was randomly selected from the blocks and interviewed using semi-structured interview schedule

2.3 Data Analysis

Data were subjected to analyses using STATA 12.0 software (STATA, 2012). Descriptive (frequency, percentage, and means) and interaction probit model analysis were used. The assertion of interaction was made because for any causal relationship claim is satisfied, there are set of conditions that need to be met. For instance, an increase in a variable x may be associated with an increase in another variable y when condition z is met but no if otherwise. Neglecting the constituted term z will result in biased that is inconsistent estimate of the parameter (Greene, 2000). Therefore, an interactive effect of some independent variable was used to constitute this condition in order to correct for this biased.

Following Ai and Norton, (2003); Norton et al., (2004) and Greene, (2010) the expected value of the dependent variable, conditional on the independent variables, is

$$E[y/x_1,x_2,z] = F(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \delta z) \quad 1$$

Where y is the dummy dependent variable, F (.) is a nonlinear conditional mean function, x_1, x_2 are variable of interest, and z is a related variable or a set of variables, including the constant term.

$$E[y/x_1,x_2,z] = prob(y = 1/x_1,x_2,z)$$
$$= \Phi(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \delta z = \Phi(A), \quad 2$$

Where $\Phi(A)$ is the standard normal cdf. The results will generate to other models with only minor modification (Ai & Norton, 2003). Partial effects in the model are

$$\partial E[y/x_1,x_2,z]/\partial x_1 = \Phi'(A) \times \partial A/\partial x_1 \quad 3$$

$$= \Phi(A) \times (\beta_1 + \beta_2 x_2,$$

For a continuous variable, where $\Phi(A)$ is the standard normal pdf, or

$$\Delta E[y/x_1, x_2, z]/\Delta x_1 = E[y/x_1 = 1, x_2, z] = E[y/x_1 = 0, x_2, z] \quad 4$$
$$= \Phi(\beta_1 + \beta_2 x_2 + \beta_{12} x_2 + \partial z) - \Phi(\beta_2 x_2 + \partial z$$

For binary variable, the interaction effect is the effect of a change in one of the variable on the partial effect of the other variable: for two continuous variables,

$$\frac{\partial^2 E[\frac{y}{x_1}, x_2, z]}{\partial x_1 \partial x_2} = \beta_{12}\Phi'(A) + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)\Phi'(A) \quad 5$$
$$= \beta_{12}\Phi(A) + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)[-A\Phi(A)].$$

Differentiation is replaced with differencing when the variables are binary:

$$\frac{\partial(\Delta E[y/x_1, x_2, z]/\Delta x_1}{\partial x_2} = (\beta_2 + \beta_{12})\Phi(\beta_1 + \beta_2 x_2 + \beta_{12} + \partial z)$$
$$= \beta_2 \Phi(\beta_2 x_2 + \partial z)$$

Or

$$\Delta^2 E[y/x_1, x_2, z] = [\Phi(\beta_1 + \beta_2 + \beta_{12} + \partial z) - \Phi(\beta_2 + \partial z]$$
$$-[\Phi(\beta_1 + \partial z) - \Phi(\partial z)]$$

However, the coefficient on the interaction term, β_{12}, does not produce the change in the partial effect of either variable on the conditional mean function if the function is nonlinear. Even after scaling by $\Phi(A)$ as in equation 3, the wrong measured interaction on effect, $\Phi(A)\beta_{12}$, which is what is likely to be reported by software that reports partial effect in form of scaled coefficients, does not provide a useful measure of any interacting quantity.

3. Result and Discussion

Table 1 shows descriptive statistics of farmer's perception in relation to socio-economic characteristics. It reveals that (89.9%) the male respondent perceived the change in climate while about 70% of the female respondents perceived that there is a change in climate.

Table 1: Perception of climate change by households characteristics

Household characteristics	Perception of climate change (%) No	yes
Gender		
Female	29.3	70.7
Male	10.1	89.9
Education		
No education	13.3	86.7
Primary	19.1	82.9
Secondary	14.7	85.3
ND/NCE	21.4	78.6
HND/BSC	8.3	91.7
MSC/PHD	0	100
Age		
<=30	0	100
31 -60	14.6	85.4
>60	23.5	76.5
Marital status		
Single	0	100
Married	13.8	86.2
Divorced	33.3	66.7
widowed	40.0	60.0
Access to extension agent		
Yes	14.0	86.0
No	14.6	85.4
Farming Experience		
≤10	16.4	83.6

Household characteristics	Perception of climate change (%)	
	No	yes
11 – 20	16.0	84.0
21 – 30	7.7	92.3
31 – 40	11.5	88.5
>40	18.2	81.8
Farm size		
≤2	13.3	86.7
3 – 4	19.1	80.9
≥4	13.0	87.0
Income		
<500000	15.7	84.3
500000 – 1000000	14.8	85.2
>1000000	0	100

Also, all educated people assumed that they have perceived change in climate, this may be as a result of their ability to access information through reading. It seems that the less the access of farmer to extension agents and the age of the farmers, the more likely they are to claim that they have perceived change in the climate. It also seems that the more experience farmers have, the more likely they are to claim that the climate have change. Maddison, (2007) confirmed that as experience increases farmers are more likely to claim that there is less rainfall, more likely to notice changes in the timing of the rains and more likely to notice a change in the frequency of droughts. The results for income are very similar: once again the more the income of the farmers, the more they claim they perceive climate change.

Unfortunately, table 1 did not indicate any causal relationship between climate change perception and all the various factors indicated. Nor does it indicate whether the results are statistically significant. Table 2 present the results of analyses for diver's factors of climate change perception using interaction probit regression. The interaction probit regression models produced good fits as revealed by statistical significance ($p<0.01$) of the Likelihood Ratio Chi Square. The binary response of climate change perception is regressed on a range of variables including age, gender, years of education, farmer experience, farm size, income, access to credit, contact with extension agent, and climate information. We also include data on if the farmer have been affected by the climate related risks such as increased in temperature, incidence of pest, occurrence of flood and drought.

Table 2: The probability of perceiving climate as a function of farmer characteristics

		Model 1	**model 2**	**model 3**	**model 4**			
Age		-0.047**	-0.068**	-0.065**	-0.075*			
Male		0.513		--0.637		1.221***		0.289
Education Level	0.112		0.255		2.106***		1.980***	
Farm Experience	0.047**	0.045**	0.063***		0.063***			
Farm Size		-0.016		-0.017		0.729**	0.707**	
Income		0.000		0.000		0.000		0.000
Credit Access		0.437		0.390		0.667		0.688
Extension		-0.376		-0.314		-0.909*	0.895*	
Climate Information		0.800*		0.634		1.126**	1.082**	
Increased Temperature	1.713***		1.694***		2.384***		2.358***	
Pest		1.111***		1.067***		1.643***		1.629***
Flood		1.299***		1.233**	1.677***		1.649***	
Drought	-1.384***		-1.257**	-1.601***		-1.580***		
Constant	-0.543		0.067		-6.597		-1.580*	
Interaction terms								
Male x Education	0.194						0.092	
Male x Age				0.036				0.013
Education x farm size						-0.259***		-0.251***

*** Significant at 1% level ** significant at 5% level * significant at 10% level

The model was run four times, with an interaction between male and educational level, male and age, educational level and farm size and inclusion of all the interaction variables. The statistical significance of the partial effects of the interaction variables such as Age, farm experience, climate information, and increase in temperature, incidence of pest, occurrence of flood and drought are significant in model 1. Also, age, farm experience, increases in temperature, incidence of pest, occurrence of flood and drought were significant in model 2. Age, education, farm experience, farm size, contact with extension agent, access to climate information, increases in temperature, incidence of pest, occurrence of flood, drought and the interaction of education and farm size were significant in model 3. Lastly, age, educational level, farm size, contact with extension, access to climate information, increases in temperature, incidence of pest, occurrence of flood, drought and interaction of education and farm size were significant in model 4, which included all the interaction variables.

The significant of interaction variable in table 2 seem necessary but not sufficient (Ai and Norton, 2003). One of the major issue relating to this interpretation of partial effect interaction variables is the accommodating of the unit of measurement such as continuous variables age and farm size. However, the economic content of the results is shown in the figures below which hints the impacts of interaction variables. Both partial interaction effect of age and educational level, and that male and age are not statistically significant at conventional levels, so with this, we could conclude from such results that the interaction effect is basically zero. Nonetheless, we could see from the graphical representation the magnitude and statistical significance ranges widely. Despite the lack of statistical significance of the coefficient on the interaction terms, the full interaction effect is large and statistically significant for many observations (see figures 1 and 2). This shows that only looking at the table of results can be deceptive.

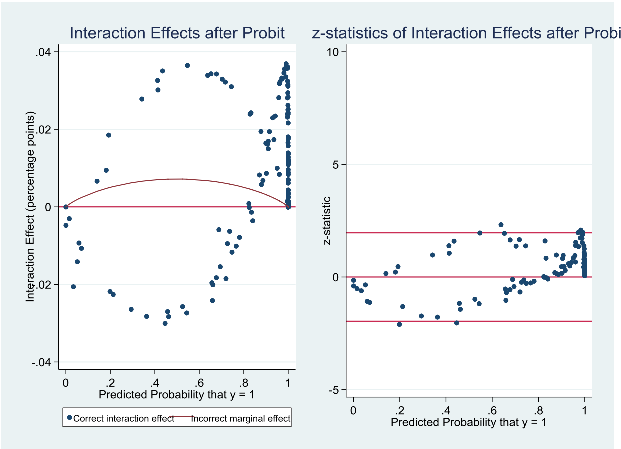

Fig. 1. Interaction effect as a function of the predicted probability and *t*-Statistic as a function of the predicted probability for model 1.

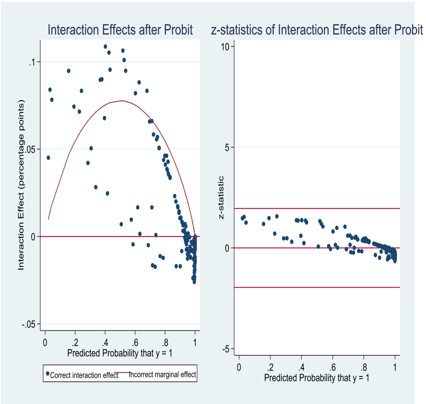

Fig. 2. Interaction effect as a function of the predicted probability and *t*-Statistic as a function of the predicted probability for model 2.

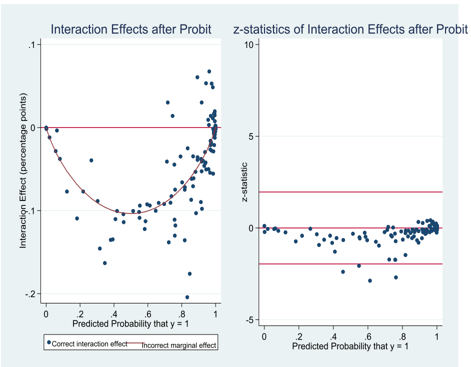

Fig. 3. Interaction effect as a function of the predicted probability and *t*-Statistic as a function of the predicted probability for model 3.

The interaction effect depends on other covariates. For example, for people whose predicted probability of perceiving change in climate is around 0.2 (toward the left end of figure 2), the interaction effect of educated male is positive for all of them while at the right side of figure 2, where people have a predicted probability of perceiving change in climate around 0.8, their interaction effects are mostly negative. In terms of the significance of the interaction effects, for both left group of people whose predicted probability is about 0.2 and for the right group of people whose predicted probability is around 0.8, the interaction effects are all significant. The coefficient of educational level, farm size and their interaction effect are statistically significant in model 3. This imply that persons who are more educated and have more farm size are more likely to perceive the change in the climate. Although, after running the marginal effect, the mean interaction effect is negative (-.029173) and varies widely. For few observations, the interaction effect is positive while most others observations is negative (see figure 3)

Conclusion

Several scholars of climate change perception have based their analysis on simple linear- additive model, whereas in real world setting some variable interact to bring a significant change. Although, few scholars are becoming increasingly aware of this mistake and are now frequently including interactions in their analyses (Bramor et al., 2006; Franzese, 2003). In this article, we have showed the interaction effect of some key variables such as educational level, age, male and farm size that influence the probability of climate change perception.

Our findings emphasize that all educated people assumed that they have perceived change in climate which maybe as a result of their better access to information through reading. Also, people who are more educated and have more farm size are more likely to perceive the change in the climate. So also for the male educated. These show the need to integrate interactions among household variables in activity-based predicting models. We recommend that for effective efforts at increasing awareness and perception of climate change in rural households there is need to promote education of farming households, which will go a long way in increasing the awareness and perception of the climate change.

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