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ROLES OF SOCIAL NETWORKS IN ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES AMONG RURAL FARM HOUSEHOLDS IN SOUTHERN NIGERIA

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ABSTRACT
Social networks are usually based on trust and commitment and are important in the farm households decision-making process on adoption of new innovation. They also served as technical, moral and financial support centers for rural farm households. Climate change presents a great development challenge for the global community in general and particularly for rural farm households in developing countries. Climate-smart agriculture is one strategy aimed to help farmers in the study area adopt more sustainable farming practices. The study looked at adoption of climate-smart agricultural practices (CSAPs) and the role of social networks in the process. The objectives of the study were to describe the determinants and barriers affecting farm household adoption of CSAPs in Nigeria; and to explore how social learning and networks contributes to knowledge and decision making during adoption of CSAPs in Nigeria. Primary data were collected on socio-economic and cultural activities among rural farm households, social networks and adopted CSAPs' used on cultivated parcels using a structured questionnaire. Data were analyzed using percentages, mean and Multivariate Probit model. The multivariate model of CSAPs' results showed that determinants and constraints for the adoption of agricultural innovation existed at multiple levels. The study concluded and presented evidence of the value of social networks for the adoption of CSAPs, identified the promising social networks that influenced the adoption process. The study suggests a range of factors, such as access to market information, knowledge, social and language barriers, access to extension services, member of a social group, physical or financial access to inputs, institutional or policy support, that could be restricting farmers from adopting CSAPs.

Keywords: Adoption, Climate-smart practices, Farm households, Social network, Nigeria.

INTRODUCTION
Climate change presents a great development challenge for the global community in general and particularly for smallholder farming households in developing countries. Smallholder agriculture has a vital role to play for future food supply, as it is the most dominant sector forming about 80% of the global land and supplying 60% of the staple food in the world (Food and Agriculture Organization [FAO], 2008). Despite its role, the majority of smallholder farmers suffer from food insecurity and poverty due to excessive reliance on traditional, nature-dependent and low-productive agriculture.

It is also widely recognized that land mismanagement and resource depletion associated with limited soil and water conservation practices are the main drivers of land degradation. Adoption of new technologies (such as soil conservation, use of manure, water harvesting, tree planting and grass stripping practices), which reduce exposure to weather shocks and enhance agricultural productivity, are therefore, essential in enhancing agricultural productivity and food security (Maertens and Barrett, 2012). Being cognizant of this fact, considerable efforts have been made to rehabilitate degraded lands. For instance, the largest soil conservation measures were implemented in the 1980s with the assumption that conservation measures would halt the degradation problem and lead to sustainable land use (Bewket, 2007; Dessie *et al.* 2012; Kassie *et al.* 2012). The whole effort was, however, regarded as a failure and adoption rates remain quite low.

Climate-smart agriculture is one strategy aiming to help farmers adopt more sustainable farming practices. It integrates the three dimensions of sustainable development (economic, social and environmental) by jointly addressing the food security, ecosystems management and climate change challenges (Lipper *et al.* 2014). It comprised of three main pillars: sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; reducing and/or removing greenhouse gases emissions, where possible.

Despite low adoption rates of new agricultural technologies in Nigeria, empirical evidence supports that adoption of climate smart agriculture is crucial in reducing exposure to weather shock and increasing food security. Furthermore, studies indicate a higher potential benefit of adoption for the most vulnerable farm households (Di Falco e*t al.*, 2011). This implies that judicious management of natural resources and adoption of new farming practices are essential in increasing gains in productivity (Herrero *et al.*, 2010).

Empirical works on the determinants of adoption of sustainable resource management practices focus on: risk aversion and high opportunity costs of adoption (Yesuf, 2009; Kassie *et al.* 2012), difference in agro-ecological and climatic factors (Deressa *et al.*, 2009), heterogeneity among households in terms of socio-economic characteristics (Berger, 2001; Schreinemachers *et al.,* 2009 and 2010; Suri, 2011), profitability factors including information barrier (Foster and Rosenzweig, 1995; Munshi, 2004; Rosenzweig, 2010; Conley and Udry 2010) and supply side constraints such as credit and fertilizer (Coady, 1995; Croppenstedt *et al.*, 2003; Shiferaw *et al.*, 2008; Suri, 2011). The above-mentioned studies analyzed the determinants of technology adoption from the perspective of economic incentives paying little attention to the role of social networks. It is only recently that social network capital has gained more attention as a major determinant of adoption (Isham, 2002). Social network enhances the adoption of agricultural technologies in many ways. Rogers (1995), for example, argued that social networks and interactions help to reduce information asymmetry and transaction costs for technology adoption. In addition, networks have the potential to relax labour and financial constraints of farmers and improve their bargaining power (Kassie *et al.*, 2012). Besides, findings of Kassie *et al.* (2012), Bandiera and Rasul (2006) and Conley and Udry (2010) corroborate with the above assertion indicating that farmers learn from their networks about new technologies.

However, much has not been studied about the extent to which differences in network structure (such as differences in ability and experience among members within a given network) matter in providing opportunities to farmers to learn about new ways of sustainable resource management practices, especially in contexts where formal information providing institutions are very limited. Several questions still remain that warrant evidence-based research. For example, as to how characteristics of members in a given network affect technology adoption; whether heterogeneity in terms of unobservable factors among members affect the uptake of new technology; and whether the type and source of information matters in technology adoption. This study examined the role of social network on adoption of climate smart practices in southern Nigeria. This is necessary as part of efforts to achieve the

Sustainable Development Goals (SDGs), to take urgent action to combat climate change and its impacts (goal 13) among other goals. The study focuses on smallholder farmers because they have been identified as one of the groups most vulnerable to the adverse effect of climate change especially in Sub-Saharan region (Morton, 2007). Therefore, this article fills these research gaps by examining how the structure and the size of network affect farmers' decision to adopt climate smart agricultural practices in Southern Nigeria. The remainder of the article is organized as follows: in Section 2 deals with the study area along with the data sources and the methodology. Section 3 presents our findings and discusses the relevance of network structure for adoption of new resource management practices. Section 4 concludes and suggests policy relevant issues.

MATERIALS AND METHODS

The Study Area

The study was conducted in selected farming communities reputed for maize and rice production in Southern Nigeria. Southern Nigeria lies between longitudes 3°and 14° and latitudes 4° and 14°. It has a land mass of 206,888 sq.km and a population of 64,987,376 (National Population Commission [NPC], 2006). Southern Nigeria consists of three geopolitical zones, the South west (which consist of 6 States) of the Niger Valley lies the comparatively rugged terrain of the Yoruba highlands. Between the highlands and the ocean runs a coastal plain averaging 80 km in width from the border of Benin to the South-south, South-south is the native home of the Ijaw/Ibibio people (which consist of 6 States) separates the south western coast from the south eastern coast, is 36,000 sq km of low-lying, swampy terrain and multiple channels through which the waters of the great river empty into the ocean. South-east which is native to the Igbos (5 States) consists of low sedimentary plains that are essentially an extension of the south western coastal plains. In all, the Atlantic coastline extends for 850 km and large parts of Africa's Bight of Benin and Biafra fall along the coast. Southern Nigeria is divided into two (2) agro-ecological zones namely, rain forest and derived savannah and in addition to its huge population is endowed with significant agricultural, mineral, marine and forest resources. Its multiple vegetation zones, plentiful rain, surface water and underground water resources and moderate climatic extremes, allow for production of diverse food and cash crops. Majority of the population is involved in the production of the food crops such as cassava, maize, rice, yams, various beans and legumes, tomatoes, melons and vegetable.

Sampling Procedure

The respondents were drawn in a multi-stage sampling process as follows, the first stage was a purposive selection of three States (Cross River, Ebonyi and Ondo States) in the rain forest zone and two States (Ogun and Oyo States) in the derived savannah zone based on their level of production in maize and rice production. The second stage was by purposive selection of three (3) Agricultural Blocks per crop in each of the zones of the States. The third stage involves a purposive selection of two Extension Cells per block that is, 12 cells across six blocks among those that are located in the main area where each of rice and maize are produced in the States. The final stage was by random selection of seven (7) members of the rice/maize farmers' groups in each of the selected cells. This process yielded a total of 521 farm households. These households were made up of 673 men and 568 women that were economically active 18 years and above) as at the time of interview.

Method of Data Analysis

Data were analyzed using mean and Multivariate Probit model of climate-smart practices.

1. Multivariate probit model:

The study focused on four (4) climate smart practices which are relevant to cereal production in the Southern Nigeria and they are farmyard manuring/composting (F), Crop rotation(C), minimum tillage (M) and agroforestry (A), Multivariate Probit Model was used to analyse this objective.

2. Modelling decision to adopt CSPs:

The study assumes that each plot manager (i.e. individual farmer) compares the CSPs with the traditional technology and adopts it if he/she perceives that the expected utility from adoption exceeds the utility of the traditional technology (Awotide *et al*., 2016). Furthermore, it was assumed that farmers make multiple adoption decisions at the same time thus, this study utilized the multivariate Probit model and a set of explanatory variables on each of the different CSPs by estimating a set of binary Probit models simultaneously. The MVP model for multivariate choice decision problems can be represented by two systems of equations. First, a system of equations with latent (unobservable) dependent variables are described by a linear function of a set of observed households (*h*) and plot (*p*) characteristics (Xhp) and multivariate normally distributed stochastic terms (εhp). The second equation described the observable dichotomous choice variables. The basic model is specified as:

$$Y_k^* = X\beta_k + \mathcal{E} \quad (where\ k = F, C\ , M, A) \qquad \ldots(1)$$

The second equation describing the observable dichotomous choice variables of farmers was given as:

$$Y_k = \int_0^1 {}^{if\ Y_{npk}^* > 0}_{otherwise} \qquad \ldots(2)$$

where;

Y_k^*; denotes the latent dependent variables which can be represented by the level of expected benefit and/or utility derived from adoption. Y_k is the adoption of the k^{th} CSA practices by farmer: F = Farmyard manuring/composting (1 if adopted, 0 otherwise), C = Crop rotation (1 if adopted, 0 otherwise), M= Minimum tillage (1 if adopted, 0 otherwise), A= Agroforestry (1 if adopted, 0 otherwise), ε = Error term, p = Farm characteristics.

The explanatory variables are:

h = Household characteristics: X_1 = Age of farmer (years), X_2 = Sex of plot owner (1 = Female, 0 otherwise), X_3 = Household size (number of persons), X_4 = Access to market (if yes = 1, 0 otherwise), X_5 = Access to extension service (if yes = 1, otherwise 0) X_6 = Years of formal education, X_7 = Participation in off farm activity (if yes = 1, otherwise 0), X_8 = Member of cooperative society (1 = member, 0 otherwise) X_9 = Member of Informal group (1 = member, 0 otherwise) X_{10} = member of formal group (1 = member, 0 otherwise) X_{11} = Land type (1 = lowland, 0 = upland), X_{12} = Land acquisition mode (1 = inherited, 0 otherwise; purchased = 1, 0 otherwise; communal=1, 0 otherwise), X_{13} = Tenure duration (Short term duration = 1, 0 otherwise; Medium term duration = 1, 0 otherwise long term duration was used as reference category) X_{14} = Livestock wealth in tropical livestock unit(TLU) measured following Beyene and Muche (2010) by assigning to adult of each animal a weight to arrive at equivalent animal units: 0.7 for cattle, 0.1 for sheep, goats and pigs and 0.01 for poultry (Note, 1 horse = 1TLU).

RESULTS AND DISCUSSION

The summary statistics of the major variables used for the regression analysis is given in Table 1. Our dependent variables include the adoption of climate smart practices such as use of compost, crop rotation, minimum tillage and agroforestry. Farmers in the study area were mainly of the view that climate change is happening and affecting their crops and livelihoods mostly in a negative sense. However, adoption of climate smart practices varies across the study area depending on the nature of climate risks and exposure of farmers to formal and informal groups. In response to the perceived changes, farmers adapt various climate smart practices to mitigate against the effect of climate change. Overall, 63% of the cereal farmers adopted the use of minimum tillage. Few farmers also adopted use of compost (7%), crop rotation (7%) and agroforestry (10%) as climate smart practices in southern Nigeria. In the multivariate Probit regression analysis, we included household characteristics which are relevant for the adoption of climate smart practices. These variables include household size, age, sex and educational attainments. The average household size is about 6 members and 86% of them are male-headed households. Educational attainment level is averaging about 8 years, this indicates that majority of farmers have appreciable formal knowledge to understand and implement climate-smart agricultural technologies promoted in the area.

Table 1: Summary Statistics of Variables

Variable	Mean	Std. deviation
Age of household head (Years)	47.08	12.51
Gender of household head (1 = Female, 0 = Male)	0.14	0.34
Household size (Number of persons)	6.35	3.90
Access to market (1 = Yes, 0 = No)	0.90	0.30
Access to extension services (1 = Yes, 0 = No)	0.53	0.50
Years of formal education	8.26	5.58
Participation in off farm activities (1=Yes, 0 = No)	0.58	0.49
Member of cooperative society (1 = Yes, 0 = No)	0.42	0.49
Member of informal group (1 = Yes, 0 = No)	0.76	0.43
Member of formal group (1 = Yes, 0 = No)	0.41	0.49
Type of land (1 = upland, 0 = lowland)	0.34	0.48
Land acquisition (1 = inherited, 0 = No)	0.44	0.50
Land acquisition (1 = purchased, 0 = No)	0.09	0.29
Land acquisition (1 = communal, 0 = No)	0.14	0.35
Tenure duration (1 = short term use, 0 = No)	0.29	0.46
Tenure duration (1 = medium term use, 0 = No)	0.18	0.39
Total livestock holding	1.59	4.25
Use of compost	0.07	0.26
Crop rotation	0.07	0.26
Minimum tillage	0.63	0.48
Agroforestry	0.10	0.30

Source**:** Field Survey, 2017

As reported in Table 1, majority (90%) of the smallholder farmers had access to market in their community which aid the sales of their farm produce while 53% of them had access to extension services in their community. Also, 41% of the farmers belong to a formal group while 76% are members of informal group. About 34% of the respondents cultivated upland, 44% acquired their farmland through inheritance, 9% purchased, 14% cultivated their crops on communal land. On the basis of land tenure, long term tenure duration was used as the reference category while 29% and 18% have a short- and medium-term tenure, respectively.

The Multivariate Probit regression results revealed the Wald chi-square test statistics (X^2 (68) = 182.91) shows that the hypothesis that all regression coefficients in each equation are jointly equal to zero is rejected at 1% (prob>X^2 = 0.00), thus indicating the fitness of the model with the data, and the relevance of the chosen explanatory variables in explaining the model. Furthermore, the likelihood ratio test (X^2 (6) = 23.46), which test the hypothesis that the correlations between error terms of the equations are all equal to zero is also rejected at 1% (prob>X^2 = 0.0007), thus confirming the fitness of the multivariate probit model over the four distinct univariate probit models which ignore the potential correlation between the adoption decision of the different climate smart practices by the farmers.

This is supported by the correlation between error terms of the adoption decisions reported in Table 2 which displayed the correlation coefficients of the climate smart practices considered in the study. The correlation coefficients of the climate smart practices considered in the study suggested that some of the climate smart practices under consideration have positive correlations meaning that the CSPs under study complement each other in a plot where they are adopted (crop rotation and use of compost, Agroforestry and use of compost) and the negative correlations meant that the practices are substitutes (minimum tillage and use of compost, minimum tillage and crop rotation).

Table 2: Relationship between the Climate Smart Practices Adopted by Farmers

Estimator	Coefficient	Z
rho21	0.2134**	2.07
rho31	-0.2708***	-4.28
rho41	0.1707*	1.96
rho32	-0.1217*	-1.65
rho42	0.00178	0.02
rho43	-0.0291	-0.37

Note: ***, **, * represent statistical significance at 1%, 5% and 10%, respectively. 1 = Use of compost, 2 = crop rotation, 3 = minimum tillage, 4 = Agroforestry.
Source: Field Survey, 2017

Table 3 shows results from a multivariate probit regression in which we estimated the effects of the role of social networks on adoption of climate smart practices in Nigeria. Being a member of cooperative society influences the adoption of use of organic compost and minimum tillage. However, being a member of informal group influences adoption of compost and minimum tillage while being a member of a formal group influences adoption of crop rotation and agroforestry in Nigeria. The result is plausible in the case of Nigeria, as membership to formal associations provides access to modern sources of credit and input for intensifying agricultural production. This shows that in addition to social network ties, farmers are informed about the existence and implementation of new resource management practices through their various groups. In addition, having a social network was often necessary for effective knowledge sharing and support. For example, social networks provided opportunities to interact and exchange knowledge and farmers perceived that social networks contributed to raising their capacities to succeed or confidence when trying new climate smart technologies or practices. Adoption of climate smart practices is not only affected by social network size but also by household, farm and institutional characteristics. Household and demographic

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characteristics, such as household size, sex and years of formal education of farm households, are also found to be significant determinants of adoption of CSPs.

Table 3: Influence of Social Networks on Adoption of Climate Smart Practices

Variables	**Use of compost**		**Crop Rotation**		**Minimum tillage**		**Agroforestry**	
	Coef	**z**	**Coef**	**Z**	**Coef**	**z**	**Coef**	**z**
Age	-0.0072	-1.29	-0.0015	-0.29	0.0027	0.69	-0.0055	-1.21
Sex	-0.0327	-0.16	-0.4636*	-1.76	0.1699	1.26	-0.0243	-0.13
Access to extension service	-0.1787	-1.3	-0.1619	-1.15	0.0223	0.23	0.0606	0.47
Market access	-0.2609	-1.3	-0.2430	-1.2	0.1627	1.06	-0.2869	-1.54
Member of cooperative society	0.1110*	1.76	0.0325	0.22	0.1654*	1.89	0.0011	0.01
Household size	0.0097	0.59	-0.0362*	-1.65	-0.0420***	-3.15	0.0323**	2.16
Years of formal education	-0.0141	-1.08	0.0018	0.13	0.0028	0.3	-0.0198*	-1.7
Participation in off farm activity	0.0277	0.19	0.5619***	3.43	-0.0821	-0.81	-0.0761	-0.61
Member of informal group	0.5434***	2.95	0.0890	0.52	0.1643*	1.71	0.1196	0.77
Member of Formal group	-0.0133	-0.1	0.0292*	1.91	0.0521	0.52	0.1836*	1.8
Type of land	0.0403	0.29	-0.0617	-0.4	0.0133	0.13	-0.3429**	-2.39
Land acquisition (Inherited)	0.0971	0.63	-0.3573**	-2.19	-0.1924*	-1.72	-0.1801	-1.29
Land acquisition (Purchased)	-0.3494	-1.2	-0.1178	-0.48	0.0272	0.15	-0.1381	-0.64
Land acquisition (Communal)	-0.1375	-0.61	-0.2984	-1.39	0.1656	1.12	-0.4999**	-2.19
Land Tenure (Short term Use)	-0.3006*	-1.87	-0.1220	-0.73	0.7272***	6.67	-0.0401	-0.28
Land Tenure (Medium term use)	-0.2298	-1.18	0.2189	1.23	0.8414***	6.61	-0.0400	-0.23
Total Livestock holding	-0.0160	-0.82	0.0102	0.6	0.0043	0.4	-0.0315	-1.36
constant	-1.1315***	-2.54	-1.1438***	-2.83	-0.7519***	-2.55	-0.5437*	-1.67
log pseudolikelihood	-1105.7							
Wald chi2(68)	182.91							
Likelihood ratio of rho21 = rho31 = rho41 = rho32 rho42 = rho43 = chi2(6) = 23.46 prob>chi2 = 0.0007								

Note: ***, **, * represent statistical significance at 1%, 5% and 10%, respectively.
Source**:** Field Survey, 2017

From Table 3, sex has a negative significant influence on adoption of crop rotation which implies that male farmers tend to adopt crop rotation compared to women in the farm households. Household size has a negative and significant effect on the adoption of crop rotation and minimum tillage while it has a positive and significant effect on adoption of agroforestry. It implies that large households are less likely to adopt crop rotation and minimum tillage. The negative sign on the household size coefficient is in agreement with Alene *et al.*

(2008) that household size explains the family labour supply for prediction and household consumption levels. A positive sign implies that a larger household provides cheaper labour while a negative sign on the other hand means that a larger household is labour inefficient hence will rely on hired labour which will eventually increase the cost of production. They are also more likely to adopt agroforestry with the positive and significant effect. The effect of education is also negative and significant implying that educated farmers are less likely to adopt agroforestry. this implies that the probability of adopting agroforestry decreases if the farmer has no formal education. This means that highly educated farmers are better adopters, one cogent reason for this is that with an increase in the number of years of education, the ability of farmers to use resources efficiently increases. Allocative effect of education also enhances farmer's ability to obtain, analyze and interpret information. Short term tenure use has a negative influence on use of crop rotation and positive influence on minimum tillage this is because land occupants can only plan for short term because they are not assured of future returns on their investment (Kasie, 2017; Gido, 2012). This may also result in reluctance of farmers to invest on the land, while uncertain about their tenure and property rights on it. Medium term tenure has a positive influence on adoption of minimum tillage in Southern Nigeria.

CONCLUSION AND RECOMMENDATIONS

The study investigated the effects of roles of social networks on the adoption of climate smart practices. The result strongly suggests that social network is a very critical factor of technology (climate smart agricultural practices) adoption. In the absence of formal information sources, promoting social networks, informal community structures and social ties will therefore be important for the adoption of new technologies. Policy intervention should therefore consider the crucial role of informal social network ties as a source of timely information for farmers in Southern Nigeria.

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