Selected Poster/Paper prepared for presentation at the Agricultural & Applied Economics Association's 2017 AAEA Annual Meeting, Chicago, Illinois, July 30-August 1, 2017

Adaptation to Climate Change and its Influence on Household Welfare in Ghana

Abstract

Climate change continues to pose a serious threat to rain-fed agriculture, especially food crop production in Ghana. In this study, we examined the factors that affect farmers' decision to adopt climate sensitive farming practices to adjust to climate change and how adaptation impacts on farm productivity and household welfare. The study employed data from a survey conducted during the 2015/2016 cropping season in twenty-five communities across three regions of Ghana. We employed an endogenous switching regression approach to account for selectivity bias caused by observable and unobservable factors and to capture the differential welfare impacts of adaptation on adapters and non-adapters. The results showed that long-term mean temperature, extension contacts, farm and household endowments are the main determinants of adaptation. The results also showed that adaptation had positive and significant effects on farm incomes and household dietary diversity scores. We recommend the facilitation of access to inputs such as drought tolerant and early maturing crop varieties and fertilizer to ease adaptation challenges of farmers; in addition to the strengthening of extension service and incorporation of climate change sensitization into extension delivery.

Key words: *climate change adaptation, endogenous switching regression, household welfare, food security, Ghana*

1.0 Introduction

Many studies on climate impact assessment (eg. Hijmans, 2003; Jones and Thornton, 2003; Claessens *et al.*, 2011) indicate that SSA's crop and livestock yields will decline if there is no adaptation to future climatic conditions. Analysis of national climate data (1960-2000) shows a progressive rise in temperature and decrease in mean annual rainfall in all agro-ecological zones in Ghana (Kunstmann and Yung, 2005). However, some studies have shown that, the use of heat-tolerant maize could produce yield increase of up to 30.5% in savanna and transitional zones of Ghana under future climate change (Tachie-Obeng, *et al*., 2012).

Studies have shown that farm households in SSA have undertaken various adaptation strategies such as planting new crop varieties, changing planting dates, growing drought resistant crops, use of crop insurance mechanisms, irrigation, use of short term production credit and adoption of soil and water conservation measures (Di Falco *et al*., 2011; Abdulai and Huffman, 2014; Wossen *et al*., 2014). However, there are still indications of adaptation deficit among farm households in Ghana, which makes them vulnerable to climate variability (Techie-Obeng, 2014). To reduce the adverse effects of climate variability eventually requires overcoming the existing deficits and responding to future climate variability through adaptation and policy interventions based on empirical impact analysis especially at the micro-level.

The empirical literature on farmers' adaptation to climate shocks provides several explanations for low adaptation, ranging from information barriers, credit constraints, risk perception, environmental and institutional factors to local costs and benefits (Seo and Mendelsohn, 2008; Di Falco *et al*., 2011). Several previous studies on adaptation have analyzed household adaptation decisions separately in single equation and multinomial models (e.g. Hassan and Nhemachena, 2008; Deressa *et al*., 2009). Others have evaluated the impacts of adaptation using the Ricardian approach (eg. Mendelsohn and Reinsborough, 2007).

While there appears to be ample empirical literature on adoption and diffusion of various adaptation strategies in Sub-Saharan Africa, the literature on impact of adaptation remains scanty (Abdulai and Huffman, 2014). To the extent that low rainfall negatively impacts on crop yields, and given the erratic nature of rainfall in this region, studies which address these issues would ultimately be useful to policy makers in designing agriculture and climate change adaptation policies. This study therefore aims to identify factors that affect farmers' decision to adapt to climate change in Ghana, and how adaptation impacts on farm productivity and household welfare. The use of adaptation strategies (crop choice, irrigation and soil conservation) could improve farm productivity under conditions of erratic rainfall—a critical issue in water-deficient Savannah Zone of Ghana.

This study contributes to the expanding literature on effects of climate change on smallholder agriculture by examining micro-level evidence on adaptation and farm household welfare. We investigate how farm households' decisions to implement a set of agronomic practices (crop choice, irrigation and soil conservation), impacts on farm incomes and food security. Our study differs from earlier studies (Deressa, *et al*. 2009; Di Falco *et al*., 2011) in terms of location and empirical strategy. Specifically, we employ an endogenous switching regression (ESR) approach to account for selectivity bias, and to capture the differential welfare impact of adaptation on adapters[1] and non-adapters. This approach allows us to examine the determinants of adaptation decision, and the impact of adaptation on net farm incomes and household food and nutrition security measured in terms of dietary diversity score (DDS) and food insecurity access score (FIAS). To the best of our knowledge this will be an innovation to climate literature since existing local literature is limited to single AEZ impact analyses. Linking farm yield to household nutrition security will also be useful to policy as most existing climate adaptation impact studies have often limit welfare impact of adaptation to food access using productivity (eg. Di Falco *et al*., 2011).

The rest of the paper is organized as follows. In the next section, we present Conceptual framework and estimation techniques for the study. In section 3 we present the data and description of the variables employed in the empirical strategy. The empirical results are discussed in section 4, whilst the final section highlights the main conclusions and policy implications of the study.

[1] Adapters refer to farm households using the crop choice, irrigation and soil conservation

2.0 Conceptual framework and Estimation Techniques

2.1. Adaptation decision and impact of adaptation

The literature suggests numerous econometric techniques for modeling climate change adaptation behavior of farmers and for identifying key determinants of climate adaptation decision depending on the specific objective of the study (Deressa, *et al*., 2009, Hassan and Nhemachena, 2008, Seo and Mendelson, 2008, etc.). Due to the potentially endogenous nature of adaptation, we model the decision to adapt and impact of adaptation in a two-stage framework.

Assuming that farmers are risk-neutral, in the decision-making process on whether to adapt to climate change or not, they compare the expected utility of wealth from adaptation denoted as $U_A\ (y)$ against the expected utility of wealth from non-adaptation represented as $U_{NA}\ (y)$ with expected net returns (y) representing wealth/welfare. Adaptation then occurs if $U_A\ (y) > U_{NA}\ (y)$. Thus, farmers' expected utility of adaptation can be related to a set of explanatory variables (Z) as follows:

$$U(y^*) = \gamma' Z + \varepsilon_i \qquad (1)$$

However, the utility derived from adaptation is not observable, but the choice of adaptation or non-adaptation can be observed. This can be represented by a latent variable $A(y)$ that equals 1, if the adaptation occurs (A(y) =1 if $U_A\ (y) > U_{NA}\ (y)$) and 0 otherwise ($A(y)\ = 0$ if $U_A\ (y) \leq U_{NA}\ (y)$).

The probability of adaptation may then be expressed as:

$$Pr(A = 1)\ =\ Pr(U_A(y) > U_{NA}\ \ (y))\ \ = pr\ (\varepsilon_i > -\gamma'\, Z = 1 - F(-\gamma'\, Z) \qquad (2)$$

where F is the cumulative distribution function for ε_i. The assumptions made on the functional form of F result in different models (probit/logit/liner probability) (Wooldridge, 2002).

2.2. Impact of adaptation

Estimation of the impact of adaptation on household welfare variables (i.e. farm income and food security/insecurity), based on cross-section data, is not trivial. What we cannot observe is the outcome variables for adapters, had they not adapted (counterfactual). In typical experimental studies, this problem is addressed by randomly assigning adaptation to treatment and control status, which assures that the outcome variables observed on the control households without adaptation are statistically representative of what would have occurred without adaptation (Amare et al., 2012; Kleenman and Abdulai, 2013). However, since farmers decide to adapt given the information they have, adapters and non-adapters may be systematically different.

To the extent that these differences between adapters and non-adapters could lead to potential bias, different econometric techniques (eg. instrumental variable approach, matching methods) are applied to correct for potential bias in estimating the impact of adaptation on household welfare outcomes. Common approaches in the climate change impact assessment including the agronomic model, future agricultural resource model (FARM), agro-ecological zone (AEZ) model, integrated assessment models (IAM's) and Ricardian (or cross-section) models have been used by some researchers (Darwin, 1999; Maddison, 2007 Deressa, 2009). While the first two approaches mainly rely on time series data, which are often not available in developing countries, the IAM's and Ricardian models have been widely applied in cross-sectional analyses (Antle and Valdivia, 2011; Hassan and Nhemachena, 2008; etc.). As stated earlier, the Ricardian approach has been heavily criticised because of its failure to account for potential endogeneity of adaptation and the use of change in land values to estimate welfare impacts – there exists no functional land markets in most developing countries including Ghana. Therefore, in this study, we employ endogenous switching regression (ESR) approach, because of its strength in accounting for both observable and unobservable selectivity bias.

Consider that household welfare is indicated by Y_{1i} for adapters and Y_{0i} for non-adapters. Let X_{1i} and X_{0i} be vectors of explanatory variables relevant to each group. Also let A* be a latent variable determining adaptation status, and Z a vector of explanatory variables assumed to explain the probability of adaptation as stated in equation 1. Finally, let $\boldsymbol{\varepsilon}$, $\mathbf{u}_1$, and $\mathbf{u}_2$ be error terms. The switching regressions can all be defined by the following set of equations:

$$A_i^* = 1\ (\alpha' Z_i + \varepsilon_i) \quad \text{if } [\ A_i^* > 0] \tag{3}$$

Regime 1: $y_{1i} = \beta'_{1i} X_{1i} + u_{1i},\ if\ A_i = 1$ (4a)

Regime 2: $y_{0i} = \beta'_{0i} X_{0i} + u_{0i}\ ,\ \ if\ A_i = 0$ (4b)

where β_1 and β_0 indicate individual specific parameter vectors, α a parameter vector in the selection/adaptation equation and θ parameter vector of mean plot variant covariates.

Since the decision to adopt adaptation strategy is not randomly assigned the error term of the selection (adaptation) equation ε_i might be correlated with that of the outcome equations' $u's$. That is $cov(u_i \varepsilon_i \neq 0)$. Consequently, the expected values of u_{1i} and u_{0i} conditional on sample selection can be stated as (Fuglie and Bosch, 1995; Lokshin and Sajaia, 2004):

$$\left[E(u_{1i}|\ A_i\ = 1) = \sigma_{\varepsilon 1} \frac{\emptyset(Z_i\alpha)}{\Phi(Z_i\alpha)}\right] = \sigma_{\varepsilon 1}\lambda_{1i} \tag{5a}$$

$$\left[E(u_{0i}|A_i = 0) = -\sigma_{\varepsilon 0}\frac{\emptyset(Z_i\alpha)}{1-\Phi(Z_i\alpha)}\right] = \sigma_{\varepsilon 0}\lambda_{0i} \quad (5b)$$

where $\emptyset(.)$ refers to the standard normal probability density function and $\Phi(.)$ the standard normal cumulative density function, while λ_{ji} refer to the inverse Mills' ratio. The covariance terms, $\sigma_{\varepsilon 1}$and $\sigma_{\varepsilon 0}$ will be estimated and if they are statistically significant, then the decision to apply adaptation by a farmer will be said to show evidence of endogeneity or sample selectivity bias (Madala , 1983). The next stage involves adding the selectivity terms to the outcome equations 11a and 11b to obtain:

$$y_{1i} = \beta'_{1i}X_{1i} + \sigma_{\varepsilon 1}\lambda_{1i} + \cup_{1i},\ if\ A_{i1} = 1 \quad (10a)$$

$$y_{0i} = \beta'_{0i}X_{0i} + \sigma_{\varepsilon 0}\lambda_{0i} + \cup_{0i}\ ,\ \ if\ A_i = 0 \quad (10b)$$

The expected values of the outcome y given adaptation and non-adaptation can be expressed as:

$$E(y_{i1}|A = 1) = \beta'_{i1}X_{1i} + \sigma_{1\varepsilon}\lambda_{1i} \quad (7a)$$

$$E(y_{i0}|A = 1) = \beta'_{i0}X_{0i} + \sigma_{0\varepsilon}\lambda_{1i} \quad (7b)$$

A change in the outcome due to adaptation termed the average treatment effect on the treated (ATT), is expressed below as the difference in the expected outcomes between equations (7a) and (7b) as (Lokshin and Sajaia, 2004):

$$\text{ATT} = E(y_{1i}|\ A_i = 1) - E(y_{0i}|\ A_i = 1) = (\beta_{i1} - \beta_{i0})X' + \lambda_{1i}(\sigma_{1_\varepsilon} - \sigma_{0_\varepsilon}) \quad (8)$$

Similarly, the average treatment effect on the untreated (ATU), is expressed as:

$$\text{ATU} = E(y_{1i}|\ A_i = 0) - E(y_{0i}|\ A_i = 0) = (\beta_{i1} - \beta_{i0})X' + \lambda_{0i}(\sigma_{1_\varepsilon} - \sigma_{0_\varepsilon}) \quad (9)$$

where σ represents the covariance of the error terms and λ the inverse mills ratios. Thus, the impacts of adaptation on farm income, HDDS and HFIAS can be estimated using the ESR[2].

Finally we estimate the selection and outcome equations (7) and (8) simultaneously by full information maximum likelihood (FIML) method, as it is a more efficient method to estimate endogenous switching regression models than a two-step approach (Lee and Trost, 1974). Given the assumption of the distribution of the error terms in the selection and outcome equations above, the logarithmic likelihood function can be stated as (Lokshin and Sajaia, 2004):

$$lnL_i = \sum_{i=1}^{N} A_i \left[ln\phi\left(\frac{u_{1i}}{\sigma_1}\right) - ln\sigma_1 + ln\Phi(\theta_{1i})\right] + (1 - A_i)\left[ln\phi\left(\frac{u_{2i}}{\sigma_2}\right) - ln\sigma_0 + ln\Phi(\theta_{0i})\right] \quad (10)$$

Where,

$\theta_{ji} = \frac{(Z_i\alpha + \rho_j u_{ji}/\sigma_j)}{\sqrt{1-\rho_j^2}}$, j =0, 1 and ρ_{ij} refers to the correlation coefficient between the error term in the selection equation (ε_{ij}) and the error term (u_{ij}) in the outcome equations.

3.0 Data and Descriptive Statistics

The study was carried out in Ghana with focus on smallholder farmers in three regions namely Brong-Ahafo, Northern and Upper East regions. These regions are of immense importance in food crop production in Ghana and share similar features with respect to agricultural activities; with households depending largely on rain-fed subsistence farming for their food and livelihood security.

[2] We used *movestay* in STATA written by Lokshin and Sajaia (2004) which simultaneously estimates the selection and outcome functions using FIML approach.

Using multistage sampling, 476 households were selected and interviewed across three regions; Upper East, Northern and Brong-Ahafo regions. Information was taken on general household characteristics, climate change adaptation decision, access to climate change information, land holding, the type of crops cultivated, irrigation access and various farming related activities, experience of risk and uncertainties as well as perceptions on local climate and the strategies being implemented to mitigate real or possible effects of climate change. Following existing literature on climate change impact analysis, we also captured farmer reported plot characteristics, such as soil fertility, soil drainage level, slope of land and soil type (see Di Falco et al, 2011, Kassie *et al*. 2014).

The data reveal significant differences between adopters and non-adopters of adaptation strategies. Specifically, adapters were observed to earn GHS 766 more from crop production than non-adapters. The two groups reported similar household dietary diversity scores (HDDS) but differed in their reported household food insecurity access scores (HFIAS) (3.9 and 5.2 for adapters and non-adapters respectively). Adapters were also observed to use more purchased seed, use more fertilizer and hired-labor than non-adapters (Table 1). Majority (82-85%) of household heads are men with relatively few years (5 and 6 for adapters and non-adapters, respectively) of formal education. More non-adapter households were reported to be engaged in off-farm activities. This is confirmed by the significant difference in the reported *off-farm incomes* earned by the two groups. Adapting households had larger farms than non-adapters and this could imply that farm size might play a role in adaptation. Only a few (17% and 14% adapter and non-adapters respectively) number of farmers belong to a farmers' group/association, with 42% and 35% of adapters and non-adapters reported to be credit constrained.

We used climate data (rainfall and temperature) from the Ghana Meteorological Services (GMS) and complemented it with data from the HarverstChoice climate data for Ghana for the selected districts. We then employed the *Thin Plate Spine* method[3] of spatial interpolation to determine household specific rainfall and temperature values using the household's location-specific coordinates (latitude, longitude and elevation). Several studies have used this approach in climate impact analyses at the plot or household levels (e.g., Di Falco *et al*., 2011).

3.1 Dependent Variables

Adaptation is defined to include the use of *irrigation*, use of modern varieties, drought resistant and early maturing varieties (*Crop choice*) and *Soil conservation strategies*. In their study on West African agriculture and climate change Di Falco and Veronesi (2014) observed significant impact of irrigation and other strategies on farm revenue, but irrigation alone as a strategy failed to significantly influence net revenues. Empirical results of a study by Ndamani and Watanabe (2015) using weighted average index (WAI) analysis showed that farmers in the Upper West region of Ghana ranked improved crop varieties and irrigation as the most important adaptation measures. Several studies have linked crop choice/switching crops and changing planting dates to climate change adaptation (eg. Deressa, 2009; Di Falco *et al*. 2011; Issahaku and Maharjan, 2014). Abdulai and Huffman (2014) also observed significant impact of bunding on rice yields, suggesting that the adoption of soil and water conservation strategies especially under conditions of climate uncertainty could contribute to improved farm outcomes through reduction of crop failure. During periods of drought, stone and soil bunds improve rainwater harvesting, retention and infiltration into the soil, increasing the amount of water available to plants and guaranteeing good crop harvest.

[3] The interpolation was done with the help of a trained hydrologist, working with University for Development Studies

When a good vegetation cover gradually develops on the stone bunds, they also aid to lower soil temperature, provide protection against wind erosion and help to conserve biodiversity (Kato *et al*., 2011; Zougmore, *et al*., 2014).

3.2 Welfare variables

The welfare variables considered in this adaptation evaluation include farm income and food security measured by household dietary diversity score (HDDS) and household food insecurity access scale (HFIAS). Many practices of farm households are yield-related, and they are expected to affect productivity and consequently household farm income and welfare. This study therefore, measures the effect of climate change adaptation on farm income. Gross farm income includes revenue from sale of crops, and home consumption of farm produce valued at local market prices. From Table 1, farm incomes for adapters are reportedly higher than that of non-adapters (GHS 2,731.99 and GHS 1,965.58 respectively). Several previous studies have used farm income as an indicator of household welfare (eg. Di Falco, *et al*, 2011; Bizuneh, 2013; Abdulai, 2016).

TABLE 1 HERE

Household welfare has different dimensions and therefore requires a multidimensional measurement approach as no single measure completely captures all the dimensions. In this study we employed household dietary diversity score (HDDS)[4] and household food insecurity access sores (HFIAS[5]) (indicators of household food security/insecurity), as additional welfare indicators.

[4] Household Dietary Diversity Score (HDDS) captures the number of different kinds of food or food groups that household members eat and the frequency with which they eat them. The result is a score that represents the diversity of intake, but not necessarily the quantity, though such scores have been shown to be significantly correlated with caloric adequacy measures (IFPRI, 2006, Coates *et al*. 2007).

[5] The HFIAS score is a measure of the degree of food insecurity (access) in the household in the past four weeks (30 days). The maximum score for a household is 27 (if the household response to all nine frequency-of-occurrence questions was "often", coded with response code of 3); the minimum score is 0 for a household with no reported food insecurity (better food access). Thus, the higher the score the more food insecure a household is. Coates, *et al*. (2007) indicate the usefulness of the HFIAS in determining food access especially in cross-section surveys.

From Table 1 the mean HDDS for the sample range between 6.63 and 9.90 (out of a maximum of 12). It is assumed in this study that, households using the adaptation strategies will have improved productivity as well as HDDS measures compared to non-adapting farm households.

3.3 Explanatory variables

The model specifications for this study draw on both agricultural technology adoption as well as climate adaptation literature (e.g. Abdulai and Huffmann, 2014, Kassie et al., 2015 Teklewold *et al*., 2013; Di Falco *et al*., 2011; Amare et al., 2012). Detailed descriptions of the explanatory variables and hypotheses about the effects of these variables are discussed below.

Empirical adoption studies have found mixed effects of *farm size* on adoption. For example, Hassan and Nhemachena (2008) observed a negative correlation between irrigation adoption and farm size, but a positive and a significant relationship between farm size and dry land farming as adaptation options. Plot level characteristics play a critical role in the adoption of climate sensitive practices. For instance, while Kassie *et al.* (2015) indicate positive and significant relationship between plot slope and adoption of sustainable agricultural practices, Abdulai and Binder (2006) observe no such relationship. To the extent that plot slope, drainage and soil quality affect erosion and water retention which directly influence crop growth, we hypothesize that the level of these variables will affect farmers' adaptation decision and welfare outcomes.

Increasing age could reflect experience which may enhance adaptation decision of farmers (eg. Amare *et al*., 2012), or reduction in energy with age could reduce adaptation, especially if it involves us of labor intensive practices. The average educational attainment of a household head is between 5 and 6 years of schooling for adapters and non-adapters respectively. This suggests that majority of household heads have low level of education which is hypothesized to positively/negatively affect adaptation decisions. Average household size is between 5 and 6 persons within a household. Large family size may reduce labor constraints needed for the adoption and use of labor intensive adaptation practices (Asmalu and de Graaf, 2007). It may also encourage increased investment in adaptation practices due to the higher household demand for more produce. We therefore expect the effect of household size to be positive.

In this study we proxy the wealth of the household through the household available labor, livestock ownership measured in tropical livestock units (TLU)[6] and the total reported asset number and value as well as off-farm income (Kassie *et al*., 2014, Bizuneh, 2013). We include a dummy variable [1, 0] to assess if a household member had access to an alternative source of employment (off-farm employment). Between 35% and 44% of adapters and non-adapters respectively reported having some members engaged in non-farm activities. The effect of non-farm activity on adaptation decision of the household is indeterminate. Alternative income source could enhance the acquisition of inputs to facilitate adoption of adaptation strategies. However, engaging in off-farm activities could negatively affect adoption of labor intensive strategies. Possession of livestock has been reported to influence households' capacity to adopt climate adaptation measures (Bizuneh, 2013; Kassie *et al*., 2015). Assets count and value have also been reported to influence adoption of agricultural technologies and climate adaptation decision of farm households (Abdulai, 2016; Kassie *et al*., 2014). Farmers could rely on their assets and livestock to acquire production inputs to facilitate adaptation by disposing some of the assets or using them as collateral.

[6] Tropical Livestock Units (TLU's) are livestock numbers converted to a common unit (in 2005). Conversion factors are: cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chicken = 0.01 (Harvestchoice, 2015)

Recent empirical studies have shown that farmers' social networks impact on technology adoption and well-being (Di Falco and Veronesi, 2014; Kassie *et al*. 2015). In many developing countries where information is scarce and markets do not often function properly, social capital, consisting of trust networks of cooperation, enhances the exchange of information, and facilitates farmers' access to inputs on schedule and overcome credit constraints and climate shocks. They can reduce transaction costs and improve farmers' bargaining power, helping farmers earn higher income (Kassie et al., 2015; Ma and Abdulai, 2016). This could in turn influence adaptation. We proxy extension access by number of extension visits, which could influence adaptation decisions of farmers. The number of neighbors and friends of farmers already practicing the stated adaptation strategies could also provide an incentive or disincentive to adopt a strategy. To the extent that different forms of social capital and networks could provide different services/incentive to farmers, the expected effect of social networks on the adaptation decision is therefore indeterminate apriori.

Farmers' perceived vulnerability to climate shocks have also been reported to influence their adaptation decisions (Bizuneh, 2013). We therefore included farmers' perceived vulnerabilities to drought, flood and erratic rainfall incidence. More farmers (78% and 68% adapters and non-adapters respectively) reported being vulnerable to drought.

4.0 Empirical Results

The main results of the estimations for this study are presented in this section. To properly identify the adaptation equation requires finding a set of suitable exogenous variables during the simultaneous estimation of the selection and outcome equations.

4.1 Identification strategy

To ensure identification, some of the variables included in the first stage estimation (adaptation choice) were excluded from the outcome equations. In our case we used as selection instruments in the outcome functions variables related to information and social network (group membership, access to extension services and perceived vulnerability to climate shocks). The admissibility of these instruments were tested with a falsification test (Di Falco *et al*., 2011). An instrument is said to be valid if it significantly affects adaptation decision but not the welfare outcome. Table A1 in the appendix shows that the instruments jointly and significantly influence the decision to adapt (Model $\chi^2(3) = 31.05$, $p<0.00$), but not farm income, HDDS or HFIAS [$F(3, 472) = 4.07$, $p=0.07$; $F(2, 473) = 0.60$, $p=0.547$, and $F(2, 473) = 2.46$, $p=0.086$)], respectively.

4.2 Determinants of Adaptation

The FIML ESR model involves a selection equation and separate outcome equations for adapters and non-adapters which are estimated simultaneously. The results of the estimation of equation 3 (selection equation) are about the determinants of adaptation decision and reported in column 2 of Tables 3, 4 and 5. Also, columns 3 and 4 of table 3, 4 and 5 present the estimated coefficients of farm income, HDDS and HFIAS functions respectively. The results of the estimation of equation 3 (Table 3, column 2) suggest that farmers decision to adapt some climate sensitive adaptation strategies in response to climate change are significantly influenced by fertilizer use, household assets, climate variables as well as information and vulnerability perception. Farmers who use more fertilizer or more endowed with assets are more likely to adapt. This observation is consistent with findings of earlier studies about adoption of sustainable agricultural practices (Kassie *et al*., 2014). Access to off-farm employment negatively influences adoption of adaptation strategies. This could be due to the impact of alternative employment on labor availability to undertake adaptation practices. The estimates of climate variables significantly explained adaptation behavior of farm households. Both linear and quadratic terms of temperature and rainfall significantly influence farmers' probability of adoption of adaptation strategies. This provides evidence that adaptation strategies undertaken by farmers are indeed correlated with climate variables. Similar finding have been observed in previous findings (eg. Di Falco *et al.*, 2011; Deressa *et al.*, 2009). Contact with extension agents and perceived vulnerability to drought significantly and positively correlate with probability of adaptation. These observations are consistent with similar studies by Deressa *et al*. (2009) and Bizuneh (2013) in the Nile Basin. Extension contacts are means by which farmers could obtain relevant information about adaptation practices. The probability of adaptation is also correlated with the tenure status of a plot. Farmers on rented plots are less likely to implement adaptation practices. This is observation is consistent with that of Abdulai *et al* (2011) on land tenure arrangement and farmers' investment decisions. Since the selection equation is the same for table 4 and 5, we only discuss the estimates of the outcome equations in the next section.

TABLE 2 HERE

4.3 Implications of adaptation on Farm incomes, Dietary diversity (HDDS) and Food insecurity (HFIAS)

Table 2 also shows how each of the explanatory variables affects the welfare measures (income). The estimated coefficients of correlation between adaptation decision and farm income functions ρ_j is not statistically different from zero. The non-significance of the correlation coefficient between the selection equation and farm income equations of adapters and non-adapters indicates that the hypothesis of absence of sample selectivity bias between adaptation decision and farm income may not be rejected. However, the differences in the farm income equation coefficients between adapters and non-adapters illustrate heterogeneity in our sample. That is the farm income function of adapters is significantly different from the income function of non-adapters (Table 2, columns 2 and 3). Consistent with economic theory, inputs such as weedicide significantly and statistically influenced farm incomes of both adapters and non-adapters. Hired labor however positively and statistically influenced the yield of non-adapters. This could be explained by the high proportion of non-adapters engaged in off-farm employment (Table 1) which might influence their use of hired labor for production activities. The effect of climate variables on farm income indicate an inverted-U shape for both adapters and non-adapters, the effect was however, significant for adapters with respect to precipitation-and the squared term of temperature.

Household welfare is multidimensional and different indicators have been used to measure it. Apart from farm incomes, food and nutrition security, measured as dietary diversity scores (DDS) has been used to capture the nutrition status of a household especially in surveys (Coates et al, 2007). Table 3 (columns 3 and 4) presents the ERS estimates for HDDS. Self-selectivity is observed with respect to HDDS and adaptation status among adapters and non-adapters (Table 3, column 3 and 4). Specifically ρ_1 and ρ_0 are statistically significant indicating the existence of self-selectivity bias.

TABLE 4 HERE

The significance of the likelihood ratio tests for independence of equations (Chi-sq = 5.22, p=0.02) also indicates that there is joint dependence between the selection equations and the DDS equations for adapters and non-adapters. The differences in the estimated coefficients between adapters and non-adapters indicate heterogeneity in our sample with respect to household dietary diversity scores. The estimate of the variable, age is negative and statistically significant, implying that increasing age of the household head reduces household dietary diversity. Among the inputs variables fertilizer is significantly correlated with dietary diversity. This could be linked to the positive effect of fertilizer on farm productivity. However, increasing expenditure on hired labor negatively influences HDDS of non-adapting households. Even though the effect of education on HDDS is positive, it was not statistically significant. Some studies have observed significant correlation between education and dietary diversity of the household (Gobotswang and Holmboe-Ottesen, 2005; Jones *et al*. 2014). Household assets significantly and positively correlate with HDDS especially for adapting households. The effect is not significant for non-adapters even though the coefficient is positive. Several studies have linked assets to food security through asset holdings (Thorne-Lyman *et al*., 2010). None of the climate variables significantly correlates with HDDS.

An important variable of interest is farm income which significantly correlates with DDS especially for adapters. This observation is consistent with findings of Jones *et al.* (2014) who found a strong correlation between HDDS and household agricultural earnings in Malawi. We complement the HDDS with food insecurity measure: the household food insecurity access score (HFIAS). The HFIAS score is a measure of the degree of food insecurity (access) in the household in the past four weeks (Coates, *et al*. 2007). Table 4 (columns 3 and 4) presents the estimates ERS for HFIAS. We fail to reject the presence of self-selectivity bias since the correlation coefficients ρ_1 and ρ_0 are not significant in both adapters and non-adapters FIAS equations. However, the differences of the estimated coefficients of adapters and non-adapters equations signify heterogeneity between the two groups in the sample. Among household covariates, only household size significantly correlates with HFIAS especially in the non-adapters equation. Access to off-farm income also significantly reduces food insecurity (increases food security) among adapters whilst access to aid (government/NGO) decreases food insecurity among non-adapters. The relationship between food insecurity and farm income was not significant even though the effect was negative as expected and in line with economic theory (Swindale and Bilinsky, 2006). Agro-ecological zone also significantly influences food insecurity status of households. Specifically, adapting farm households in the transitional zone are less food insecure compared to those in Guinea Savannah zone. In the case of non-adapters farm households in both Transitional zone and Sudan Savannah are more likely to suffer less food insecurity compared to those in the Guinea Savannah zone.

TABLE 5 HERE

4.4 Impact of Adaptation on Household Welfare

As explained previously, to examine the impact of adaptation on household welfare, the average treatments effects (ATT) on the expected outcomes are estimated. Table 6 presents the ATT estimates of the ESR specification for farm incomes, dietary diversity score and food insecurity access score. As opposed to the mean differences in Table 1, which do not consider the influence of confounding factors, these ATT estimates account for other confounding factors including selection bias arising from potential systematic differences between adapters and non-adapters. The results indicate that adaptation significantly increases farm productivity and dietary diversity and reduces food insecurity. Specifically, the expected farm income per household from adaptation is

7.567 (GHS1,933.332) compared to 6.908 (GHS1,000.245) from non-adaptation, representing a causal effect of increase in productivity from adaptation by 93%[7].

TABLE 6 HERE

The treatment effect on the untreated is about 18% increase in expected farm incomes (that is if non-adapters had adapted). These findings are consistent with findings of other studies (e.g. Di Falco *et al*., 2011; Abdulai and Huffman, 2014). Also, the expected HDDS per household from adaptation is 8 compared to 5 in the counterfactual case of non-adaptation which translates into 60% improvement in HDDS due to adaptation. This implies that adaptation to climate change increases the dietary quality of households through improved dietary diversity. It is also clearly shown that the treatment effect on adapters' mean HFIAS is -0.52. This is equivalent to 40% reduction in FIAS. If non-adapters had adapted their HFIAS would have decreased by 28%.

5.0 Conclusions and implications

The objective of this paper was to understand factors that affect farmers' decision to adopt climate sensitive adaptation practices in Ghana, and how adaptation impacts on farm productivity and household welfare. We employed data from a survey of farmers in the Northern, Upper East and Brong-Ahafo regions of Ghana. Using multistage sampling, 476 households were selected and interviewed across the three AEZ's. We used endogenous switching regression model to account for both observable and unobservable factors that affect farm productivity and food security.

[7] The treatment effect in the income and FIAS are interpreted as percentage difference. When the outcome variable is log-transformed, multiplying the ATT by 100 is only an approximation. The actual percentage difference is given by $100(\exp^{ATT}-1)$, where exp is exponential (e) and ATT is the average treatment effect given by the analysis of the log-transformed variable (Asfaw et al., 2012).

Analysis of the determinants of adaptation indicate that fertilizer use, household assets as well as information and vulnerability perception had positive effect on the probability of adaptation. Farmers' perception about drought, flood occurrence and number of contacts with extension personnel positively influenced adaptation decision of households. In addition rainfall had an inverted U-shaped effect on the productivity of both adapters and non-adapters. The quadratic term of rainfall had positive effect on adaptation. This could be due to the fact that most adaptation practices are carried out during the rainy season. On impact of adaptation on welfare, the empirical findings also showed that adaptation in general had positive and significant impact on farm incomes and household food security, but negative impact on food insecurity (ie. HFIAS). The results also demonstrated that, if the impact of adaptation to climate on these outcomes were estimated without accounting for observable and unobservable factors in the adaptation decision process, sample selection bias could have influenced the estimated outcomes.

Finally, we draw conclusions on the effect of climate variability and change on farm productivity and food security. On treatment effect of adaptation (ATT) it was observed that farm households that adapted tend to have higher farm incomes than those that did not adapt in the counterfactual case. We also examined the food security/insecurity impact of adaptation by estimating the effect of adaptation HDDS and HFIAS. The results showed significant increase in expected HDDS as a result of adaptation.

From a policy perspective, understanding the determinants of adoption of adaptation strategies could facilitate the design and dissemination of strategies at community, district and regional levels. The causal effect of adaptation on yields and household welfare reaffirms the potential role of climate adaptation in raising farm productivity and directly reducing rural poverty through higher farm incomes. In addition, to the extent that fertilizer use positively enhance adaptation and only few farmers applied it, we recommend that government policy on fertilizer subsidies be revisited and incorporated into climate adaptation policies.

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Table 1: Descriptions and summary statistics of the variables used in the analyses by Adaptation status

Variable	Variable description	Adapters	Non-adapters	Diff
		Mean	Mean	
Outcome variables				
Farm Income	Revenue from crop production (GHS)[a]	2731.99	1965.58	766.41*** (3.74)
HHFIAS	A score indicating frequency of consumption of less preferred foods to skipping of meals. A higher score indicates food insecurity while a zero score means food security	3.86	5.17	-1.31** (-2.81)
HDDS	HH dietary diversity score, measured by the consumptions of 12 categories of foods in the past 7 days	8.03	7.77	0.26 (0.96)
PHE	Per capita HH consump expenditure (GHS)	933.32	877.73	55.59 (0.41)
variable Inputs				
Fertilizer	Exp Fertilizer (org. and inorganic) GHS	250.534	121.975	128.56** (2.26)
weedicide	Exp on weedicide/insecticides GHS	68.663	37.459	31.20 (1.58)
HiredL_cost	Hired labour GHS	219.617	109.878	109.74* (2.14)
Head and household characteristics				
Farm_size	Total Farm size of HH in hectares	2.098	1.688	0.41** (2.87)
education1	years of formal education	5.370	5.719	-0.35 (-0.72)
HH_size	Number of people in a household	6.152	5.550	0.6* (2.00)
age	age of farmer in years	39.494	39.919	0.42 (0.32)
Gender	Male=1, female=0	0.85	0.82	0.03 (1.00)
Household assets				
Nfactivity	Farmer is engaged in non-farm activity=1, 0 otherwise	0.354	0.444	0.09* (-1.9)
Livestock	Livestock ownership in tropical livestock units (TLU)	1.890	1.740	0.15 (0.32)
N-F_income	non-farm income (GHS)	464.703	775.913	311.21* (-1.68)
Aid	Amount govt/NGO support received during the yr	89.557	201.750	112.19** (2.65)
Information and psycho-social characteristics				
Ext. visits	number of extension visits	1.044	0.638	0.406*** (3.28
Vul_drought	Farmer perceives high vulnerability to drought=1, 0 otherwise	0.775	0.688	0.09** (2.08)

Table 1 cont

Variable	Variable description	Adapters	Non-adapters	Diff
Vul_flood	Farmer perceives high vulnerability to flood=1, 0 otherwise	0.244	0.406	0.16 (-3.7)
FBO_memb	Farmer belongs to a group=1, 0 otherwise	0.168	0.138	0.03 (0.854)
Dist-Water	Distance to source drinking water (km)	0.56	0.750	-0.19 (-1.08)
plot level characteristics				
Slope	Farm land is flat to gentle slope 1, 0 otherwise	0.594	0.506	0.09 ()
Soil fertility	Fertile land 1, 0 otherwise	0.828	0.868	0.04
plot drainage	Farm land is well drained 1, 0 otherwise	0.420	0.352	0.07
Tenure type	Farmer owns plot 1, 0 otherwise	0.892	0.897	0.01

***, **, * represent 1%, 5%, and 10% significance level, respectively. T-values in parentheses
[a]Exchange rate is € 1 = GHS 4.26 at the time of the survey

Table 3: Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for Adaptation and Impact of adaptation on Farm incomes

	Selection Adaptation1 (1/0)		Adapters Farm income		Non-Adapters Farm income	
Variable	coeff	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
fert_cost	0.0003*	0.0001	$2.0x10^{-6}$	$6.0x10^{-6}$	0.0001	0.0001
seedcost	-0.023	0.037	$8.0x10^{-6}$	0.024	-0.037	0.048
weedicidcost	0.065	0.042	0.060**	0.029	0.105*	0.055
HiredL_cost	-0.010	0.031	-0.011	0.021	0.065**	0.035
Farm_size	0.063	0.054	0.117***	0.032	-0.019	0.073
education1	0.018	0.015	0.004	0.011	$6.0x10^{-6}$	0.018
HH_size	0.006	0.027	0.023	0.017	0.023	0.035
Gender	-0.0087	0.147	0.128*	0.070	0.381**	0.185
Age	0.003	0.005	-0.002	0.004	0.003	0.006
Nfactivity	-0.077***	0.142	-0.136	0.101	0.131	0.165
HH_labour	0.005	0.032	0.031	0.023	-0.039	0.036
Livestock	-0.003	0.013	-0.003	0.012	0.000	0.012
lnassetamt	0.043**	0.022	0.014	0.015	-0.037	0.031
RF	-42.505**	12.465	11.399	8.825	16.699	17.193
Tem	-72.915***	19.736	17.613	11.474	22.289	30.828
RFsq	0.104**	0.040	-0.031	0.030	-0.049	0.050
RF_Temp	0.863***	0.231	-0.211*	0.145	-0.288	0.349
Exp_cropF	-0.011	0.138	-0.121*	0.095	-0.182	0.161
Subj_AssessG	0.207	0.508	0.481	0.353	0.519	0.574
Subj_forecastB	0.480	0.300	0.064	0.218	0.100	0.342
Dist-water	-0.039	0.023	0.017	0.016	-0.017	0.032
Tenuretype	-0.873*	0.531	0.943**	0.383	0.508	0.576
Ext_visits	0.148**	0.057				
Vul_drought	0.344**	0.170				
Vul_flood	-0.214	0.162				
Const	2846.453**	759.678	-731.196	493.508	-993.678	1133.161
$\ln\sigma_1/\ln\sigma_0$			-0.257**	0.041	-0.117***	0.082
ρ_1/ρ_0			0.120	0.203	-0.221	0.408
LR test of indep. eqns. :	χ^2 (1) = 0.56 Prob > chi2 = 0.4534					
Log likelihood = -826.70893						
Wald χ^2 (29) = 109.52	Prob > χ^2 = 0.0000					

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors

Table 4: Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for Adaptation and Impact of adaptation on HDDS

	Selection Adaptation 1/0		Adapters HDDS		Non-Adapters HDDS	
Variable	Coeff	(SE)	Coef.	SE	Coef.	SE
lncrop_revenue1	0.301***	(0.074)	0.438***	(0.182)	0.344	(0.296)
Farm_size	0.070	(0.053)	-0.095	(0.095)	-0.011	(0.193)
Education	0.017	(0.015)	0.054	(0.032)	-0.003	(0.048)
HH_size	0.009	(0.024)	0.025	(0.046)	0.075	(0.091)
age	0.004	(0.005)	-0.028**	(0.011)	-0.019	(0.017)
Nfactivity	-0.138	(0.136)	0.054*	(0.297)	-0.483	(0.465)
lnassetamt	0.042	(0.022)	0.094***	(0.043)	0.047	(0.086)
lnAid	0.000	(0.000)	-0.001**	(0.000)	0.000	(0.000)
Exp_cropF	-0.014	(0.137)	-0.063	(0.283)	-0.960	(0.457)
Subj_AssessG	0.241	(0.507)	-0.673	(1.054)	-1.669	(1.633)
Subj_forecastB	0.469	(0.285)	-0.678	(0.602)	-1.464**	(0.905)
Dist_water	-0.030	(0.022)	0.008	(0.047)	0.143**	(0.081)
Ext_visit	0.106**	(0.054)				
Vul_drought	0.584**	(0.153)				
Climate	Yes (sig)		Yes (ns)		Yes(ns)	
Production inputs	Yes					
cons	2587.29**	(594.539)	1310.68	(1399.75)	-2225.09	(2574.82)
$\ln\sigma 1/ \ln\sigma 0$			0.879***	(0.077)	0.999***	(0.128)
ρ_1/ρ_0			0.611***	(0.192)	0.581**	(0.242)
LR test of indep eqns. : chi2(1) = 5.22 Prob > chi2 = 0.022						
Log likelihood	-1318.63					
Wald $chi^2(20)$ = 119.92						

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors

Table 5: Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for Adaptation and Impact of adaptation on HFIAS

	Selection Adaptation 1/0		Adapters HFIAS		Non-Adapters HFIAS	
Variable	Coeff	(SE)	Coef.	SE	Coef.	SE
Farm income (log)	-0.099***	0.146	-0.055	0.093	-0.099	0.146
Farm_size	0.069	0.053	-0.004	0.038	-0.002	0.075
education1	0.009	0.015	-0.010	0.012	-0.019	0.018
HH_size	0.011	0.025	-0.010	0.018	-0.066**	0.035
age	0.002	0.005	-0.005	0.004	0.000	0.006
Nfactivity	-0.210	0.135	-0.373***	0.120	0.070	0.187
Assets (log)	0.049**	0.022	0.001	0.020	0.079**	0.038
Aid (log)	0.000	0.000	0.000	0.000	0.000	0.000
Exp_cropF	0.033	0.136	-0.119	0.108	-0.167	0.167
Subj_AssessG	0.137	0.497	0.818**	0.403	1.170**	0.593
Subj_forecastB	0.520	0.275	1.007***	0.259	0.721**	0.378
Dist_water	-0.034	0.022	-0.026	0.019	0.015	0.030
Ext. Vists	0.148**	0.061				
Vul_drought	0.353	0.212				
Climate	no					
AEZ	yes		Yes		yes	
Production inputs	yes					
cons	-2.309	0.687	1.481	1.044	2.131***	0.821
$\ln\sigma_1 / \ln\sigma_0$			-0.115***	0.047	-0.075	0.057
ρ_1/ρ_0			0.091	0.584	0.020	0.699
LR test of Indep eqns. : chi2(1) = 0.02 Prob > chi^2 = 0.87						
Log likelihood		-893.879				
Wald chi2(18)	=	71.93				

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors

Table 6: Treatment effects of farmer Adaptation on Farm incomes, HDDS and HFIAS

Variable	Adaptation decision		ATT	t-value
	Adapting	Not adapting		
Farm incomes (log)				
Adopters	7.567	6.908	0.659***	26.781
Non-adopters (ATU)	7.297	7.132	0.166***	4.854
HDDS				
Adopters	8.031	7.414	0.617***	6.864
Non-adopters (ATU)	8.439	7.758	0.680***	5.078
HFIAS (log)				
Adopters	1.119	1.635	-0.516***	-15.55
Non-adopters (ATU)	0.985	1.315	-0.330***	-8.38

***, **, * represent 1%, 5%, and 10% significance level, respectively. T-values in parentheses

Table A1 Parameter Estimates – Test on Validity of the selection of instruments

	Model 1	Model 2	Model3	Model 4
Variable	Adaptation (1/0	Farm Income	HDDS	HFIAS
Ext. visits	0.152 (0.049)	0.078 (0.034)	0.005 (0.014)	0.0495 (0.037)
Drought vulnerability	0.407 (0.139)	0.147 (0.102)		
Flood Vulnerability	0.528 (0.133)	0.173 (0.097)	0.039 (0.0394)	0.174 (0.103)
Constant	0.164 (0.125)	7.511 (0.093)	2.133 (0.025)	1.178 (0.066)
Wald Test	χ^2=31.34	F=4.07	F=0.60	F=2.46
Sample Size	476	476	476	476