

Off-farm Climate Change Adaptation Strategies and Farm Performance: Empirical Evidence from Northern Ghana

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Ethics approval This study involving human participants was conducted in accordance with ethical research standards. Ethical approval for the study was granted by the appropriate academic review authority at the University for Development Studies, Ghana.

Statement of Participants' Consent Informed consent was obtained from all participants prior to data collection. Respondents were informed about the purpose of the study, assured of confidentiality and anonymity, and participation was entirely voluntary.

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Abstract

Climate change adaptation has been progressively expanded in the literature with various attempts made at understanding the main drivers of adaptations and how such practices affect farm performance. However, our current understanding stems primarily from climate adaptation practices at the farm level where adaptation decisions directly impact farm performance outcomes. This study investigated whether off-farm adaptation practices increase farm performance. Using primary data from 412 maize farmers across Northern Ghana, we applied a multivariate probit model to account for interdependent adaptation choices and an exponential conditional mean model to identify the causal impact of off-farm adaptation intensity on maize farm performance. We found that adoption of off-farm strategies is determined by household socio-economic characteristics (sex, age, marital status, household size, education, experience, and access to good road network), wealth and asset indicators (farm size and livestock ownership) and institutional affiliation variables (access to climate smart training, climate information, and extension service). Additionally, our results indicate that combining multiple off-farm CCAS such as livelihood diversification, NGO support, remittance and crop weather insurance, is expected to decrease maize production by 15%. Based on these findings, we suggest that efforts to promote off-farm CCAS adoption should be designed with complementary measures such as labor-saving technologies to avoid potential tradeoffs in farm performance.

Keywords: Off-farm Climate Adaptation, Multivariate Probit, IV Poisson, Maize farmers, Northern Ghana.

1. Introduction

Climate change is arguably one of the biggest challenges in the 21st century and in the history of mankind. It affects nearly all aspects that depend on water use systems and consequently, agriculture which heavily relies on such systems is more vulnerable (Intergovernmental Panel on Climate Change [IPCC] 2022) due to rainfall variability, temperature changes, and extreme weather events (Mensah et al. 2025; Food and Agriculture Organization [FAO] 2023). Indeed, empirical evidence points out that agriculture is more sensitive to climate change than other sectors in developing countries (Chancel et al. 2023) and since there is no universal solution to climate change (Pinkse and Kolk 2010), adaptation has become essential and the surest way to cope with the worsening impacts of climate change.

Climate change adaptation, described as adjusting systems to climate effects to moderate harm or exploit benefits (IPCC, 2022) has been undeniably impactful, helping farmers to cope with, adjust to, and mitigate climate risk. It fundamentally shapes farm performance (Issahaku et al. 2021), reduces multidimensional poverty (Issahaku et al. 2021) and improves household welfare (Shahzad & Abdulai 2021; Issahaku et al. 2021; Martey et al. 2021). Adaptation to climate change as an “umbrella” term comprises of strategies that range from the farm level such as soil and water conservation practices (Issahaku & Abdulai 2020), uptake of improved seed varieties and changes in planting dates (Kangah & Boateng Agyenim 2022) to off-farm strategies including, petty trading, agro-processing, and poultry/livestock keeping (Yiridomoh et al. 2021) participation in Village Savings and Loans Associations (VSLA) and relying on weather forecast information (Kangah & Boateng Agyenim 2022).

Research on climate adaptation, as a field of inquiry, has been progressively expanded in literature and predominantly focused on on-farm climate change adaptation practices (Adzawla & Alhassan 2021; Issahaku et al. 2021) where adaptation decisions are said to positively correlate with farm performance (Issahaku & Abdulai 2020; Adzawla & Alhassan 2021; Issahaku et al. 2021; Kangah & Boateng Agyenim 2022). While there is a large consensus about the effects of on-farm climate change adaptation strategies (CCAS) on farm performance, there is little to none on the effect of off-farm CCAS on farm performance. Yiridomoh et al. (2022) attempted to broaden our understanding of off-farm CCAS and their effectiveness in mitigating climate risk but failed to assess how off-farm adaptation strategies affect agricultural farm performance outcomes.

In this regard, this current study aims to contribute to understanding the role of off-farm climate adaptation and farm performance and to lay the foundation for future research in climate adaptation, as a field of inquiry, by reflecting on whether adoption decision of off-farm climate adaptation decisions among small farmers in northern are mutually inclusive or exclusive and by exploring the relationships between adoption intensity of

off-farm CCAS and farm performance. For the purposes of this study, we define adoption intensity of off-farm CCAS as the number of practices a farm household head adopted over the last three cropping seasons. While performance effects of on-farm CCAS are relevant, it is also imperative to understand the causal impact of off-farm CCAS as a package on maize farm performance.

Maize is the largest food crop in Ghana and the third most widely cultivated food crop in the world (Ahmad et al. 2020). Maize is predominantly cultivated on a smallholder basis under rain fed agriculture in Ghana. Its production is useful as a source of biofuel, food and money for farmers across the world. However, climate models have shown that there will be a 29% drop in maize production by mid-century (Ahmad et al. 2020), with some projections indicating a 55% drop by the same mid-century (Barimah et al. 2014). According to the Statistics, Research and Information Directorate (SRID) of the Ministry of Food and Agriculture (MoFA) (2022), the average maize yield in Ghana was 2.53 metric tonnes per hectare (MT/Ha) in 2021. However, this figure is still much lower than the national average potential yield of 5.5 MT/Ha (MoFA, 2022). It is thought that adopting measures to adapt to climate change will increase the amount of maize produced by 12–17% (Ahmad et al. 2020). Therefore, we investigate whether off-farm CCAS contribute to enhancing farm performance among smallholder maize farmers across northern Ghana. In our investigation, we use the multivariate probit model and exponential conditional mean model to empirically identify whether farmers make a joint decision to adopt off-farm CCAS strategies and whether off-farm CCAS improves farm performance as in the case of on-farm CCAS. To achieve the research goal set forth, this work was guided by two underlying research questions:

1. **RQ1:** Are farmers' decisions to adopt off-farm climate adaptation strategies mutually dependent or independent?
2. **RQ2:** Does the adoption of off-farm climate adaptation practices improve farm performance?

By addressing these research questions, we contribute to the literature in two important ways; (1) as research on climate adaptation measures continues to expand, we shifted the analytical focus from on-farm CCAS to empirically examine whether farmers' decisions to adopt off-farm CCAS are mutually dependent or independent, and (2) we estimate the causal impact of off-farm climate adaptation intensity on maize productivity which was used as a proxy for farm performance. In analyzing the potential relationship, we provided an empirically substantiated basis for policy and practice, to treat off-farm CCAS as complementary means for adjusting to climate risk and call for the need for central understanding of the role of off-farm CCAS and performance in specific contexts.

The rest of the paper is structured in the order as follows: Section 2 introduces the theoretical background and conceptual framework of the research. Section 3 provides a detailed overview of the research methodology; Section 4 presents the results; Section 5 contains discussions of the findings in detail while section 6 provides conclusions and recommendations for practice and future research.

2.0 Theoretical /Conceptual Anchoring

2.1 Climate Change Adaptation

Definitions of climate adaptation have received various scholarly opinions. Recent literature speaks of climate adaptation as actions that mitigate the harm caused by climate change (Orlove 2022; Schipper 2020) and as a character of a public or investment good (Moser et al. 2013). While the term 'climate adaptation' is defined in different ways by different authors and in different contexts, there is a high level of agreement among scholars regarding the definition proposed by the IPCC (Guillén-Bolaños et al. 2022). The IPCC's Working Group VI (IPCC, 2022) defines climate adaptation as “*The process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects*”. Typically, moderating climate harm or adjusting to natural systems, requires some level of effort, and a broad range of actions undertaken by smallholder farmers both at the farm and off- farm levels.

On-farm climate adaptation strategy for this paper refers to the production techniques, technological and managerial strategies adopted by farm households to increase their productivity resulting from anticipated low yield of climate variability. On-farm adaptation measures typically include a variety of activities, such as using improved varieties that mature early or are drought-tolerant, replanting, applying external inputs such as fertilizer, shifting planting dates, implementing conservation agricultural practices, diversifying crops, intensifying crops, and treating crop pests and diseases (Ali 2021; Azumah et al. 2020; Issahaku & Abdul Rahaman 2019; Fagariba et al. 2018). On the other hand, off-farm CCAS are activities outside food crops

production that help smallholder farmers to adapt to the changing climate (Yiridomoh et al. 2019). These activities range from petty trading, agro-processing, poultry and livestock keeping (Yiridomoh et al. 2021), to migration (Fielmua et al. 2017; Vinkeet et al. 2020) and reliance on remittances from relatives (Musah-Surugu et al. 2018). It is important to note that although both on-farm and off-farm climate adaptation help farmers to cope with climate change, they differ in different ways; 1) by their nature, and 2) by their underlying goals. On-farm climate activities focus on minimizing climate risk so that farmers will have increased yield whereas farmers adapt off-farm activities as a way of livelihood addition to “augment the household income” and/or to “diversify their incomes” (Hassan & Knight 2023) and as insurance against agricultural risks (Antwi-Agyei et al. 2014) that enhances their resilience to negative effects of climate change (Hassan & Knight 2023). In this direction, off-farm climate adaptation emerges as a rational response to climate risk, however, such adaptation practices could also impose production trade-offs in Ghana, and Africa in general, through the non-separable agricultural farm household model, which assume that production and consumption decision are well interlinked due to imperfect market conditions such as missing labor markets.

2.2 Household climate adaptation portfolios and adaptation decision-making

When the adverse effects of climate change become more severe, agricultural households choose a mix of climate adaptation strategies to adapt to climate change, rather than relying on a specific strategy (Adzawla & Alhassan 2021). This is because they can take advantage of the fact that different off-farm CCAS can be used together or in place of each other. The choice(s) of which adaptation strategy to take generally follow three principles in climate adaptation decision making framework; complementarity, where a farmer decision to adopt a specific off-farm adaptation strategy increases the effectiveness of adopting others; substitutability, where a farmer completely or partially replace one strategy for another; and interdependence, where different adoption choices are jointly influenced by common unobserved household and contextual factors. Among these principles various studies have shown that farmers climate adaptation decisions are complementary (Adego & Woldie 2022; Bedeke, et al. 2019; Ali 2021) and are influenced by a broad range of socio-economic characteristics such as age, experience, livestock ownerships and household size (Adamseged & Kebede 2023). Because farmers are rational economic agents who aim to derive maximum benefits or satisfaction (Umar, 2014), their climate adaptation decisions to adopt or not to adopt an off-farm climate adaptation is based on the expected net benefits driven from the practice. Based on this, the farmer will only adopt an off-farm climate adaptation practice if the expected utility resulting from the practice is greater than if the practice was not adopted at all. However, the decision to adopt a *k*th adaptation strategy cannot be measured directly. On the other hand, specific choices of which adaptation farmers adopted are directly observed.

2.3 Adaptation intensity, and farm performance

Adaptation intensity in this context implies the marginal decision of a farmer to add additional strategies to an existing portfolio of CCAS that a farm household head has adopted with the objective of adapting to the variability of the climate. Given that farmers' adaptation decisions tend to rely primarily on the expected benefits, increasing intensity of off-farm CCAS has the potential to introduce diminishing returns and threshold effects in farm performance outcomes. Despite the potential benefits of off-farm activities, such as the relaxation of liquidity constraints or the provision of insurance against climate shocks (Antwi-Agyei et al. 2014), it is imperative to consider the potential adverse consequences of higher adaptation intensity in terms of increased opportunity cost. Consequently, as adaptation intensity increases, the marginal benefit of adopting an additional off-farm strategy is likely to decrease, while the marginal cost, defined as the foregone farm labor, delayed farm operations, and stretched managerial capacity increases (Saqib et al. 2025). In this case, the relationship between off-farm climate adaptation intensity and farm performance is expected to be negative because any additional off-farm strategy adopted has the potential to diminish agricultural output by intensifying labor competition and eroding farm management effectiveness.

From another vantage point, as pointed out by Mathenge & Tschirley (Mathenge & Tschirley 2008) adopting several climate adaptation practices could provide household heads with more funds to invest in farm inputs and intensification. In this reasoning, it could be seen that increasing adaptation intensity signifies the presence of a diversified source of income at the household level which may empower such a household to allocate resources toward the acquisition of agricultural inputs to increase farm productivity. Within these dissecting views, the net effect of off-farm CCAS, therefore, becomes an empirical question, as the balance

between these two theoretical stand points will determine the ultimate impact on farm performance. Hence, any correlation between the adaptation intensity of off-farm CCAS and farm performance is plausible and should not be regarded as an analogous outcome.

2.4 Empirical expectations and hypotheses

Based on theoretical anchoring in adaptation portfolio decision-making, increased time labor competition of off-farm under agricultural household production theory and diminishing returns of marginal diversification, the following a priori expectations were made prior to the estimation of the results. We hypothesized that the adoption of off-farm CCAS among smallholder farmers in northern regions is complementary, as seen in prior studies which confirmed that the decision to adopt climate adaptation strategies is complementary. Also, we expected that higher adoption intensity would be associated with higher expected maize output conditional on other factors. This is because greater uptake of off-farm CCAS could lead to higher income and reinvestment in production activities, enabling farmers to mitigate production risk and improve their farm performance outcomes. However, while we expected a positive association, the reverse is possible under a diminishing rate of marginal returns to diversification and in a non-separable agricultural farm household framework due to potential labor trade-offs.

3.0 Materials and Methods

3.1 Study Area, Sampling, and Data Collection

The research was carried out in four administrative regions of Ghana covering the Upper regions [Upper East (UE) and Upper West (UW)], North-East, and Northern regions. These regions are located within the guinea savannah agro-ecological zone and semi-arid climatic region with erratic rainfall patterns and high temperatures during the harmattan (dry) season. Together with the Bono East, Bono, and Oti regions, these regions were identified as agricultural production zones under climate stress in Ghana under the Emergency drought-spell response program by the Ministry of Gender and Local Development in 2023. However, the adverse effects of climate change are not evenly spread. The five regions of the north in Ghana have a unimodal rainfall pattern, while the middle belt, including the Bono East, Bono, and Oti regions, is partly unimodal. As such, it was outside the purview of this study to examine how off-farm climate change adaptation affects farm performance in the middle belt, rather, it focused on the most extreme regions with climate vulnerability in Ghana. Like other regions, the most cultivated crops in the study areas are maize, rice, soybeans, sorghum, and millet. Among which maize doubles as the most cultivated cereal crop in Ghana, accounting for almost half of the country's total cereal crop production (MoFA 2021) and serving as a food security staple in the areas. Within each region, one district (including Sissala East, Kassena-Nakana, Mamprugu-Moagduri, and Gushegu) was identified with the help of the local agriculture extension officers under the Department of Food and Agriculture (MoFA) based on the relative importance of maize and agricultural production activities. The sampling units comprises households, represented by the household heads.

3.2 Sample Determination

The sample size ($n = 385$) was estimated based on an infinite population using Cochran's sample determination formula (See Equation 1).

$$n = \frac{z^2 pq}{e^2} \quad \text{eq. 1}$$

$$\text{Such that: } n = \frac{1.96^2 (0.50) (0.50)}{0.05^2} = 385$$

Where:

1. n = sample size,
2. e = Margin of error (the desired level of precision), pegged at 5%, (0.05)
3. p = Population proportion pegged at 50%,
4. $q = 1 - p$ and
5. z = Z-score (the number of standard deviations from the mean, based on the desired confidence level) is pegged at 1.96 for the 95% confidence interval.

The estimated sample ($n = 385$) was adjusted to 412 to account for any possible design effect, and to ensure proportional allocation of 103 respondents per district. This approach was employed to randomly select up to

103 households and 103 respondents in each district, implying that there were a total of 412 households and 412 participants for the study.

3.3 Correlated Binary decisions, Endogeneity Issue, Model Selection and Specification

The effects of climate change, according to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2022) are being “felt in almost every aspect that depends on water use, more so in agriculture.” In order to reduce the climate-induced risks and vulnerabilities, farmers may employ diverse strategies or single select a particular adaptation strategy. However, the adverse effects of climate change become so intense, farmers' decision to adopt a particular CCAS is seldom done in isolation. That is, farmers can adopt multiple CCAS, such that the adoption of one CCAS may be linked with their decisions to adopt other improved practices. As for example, a remittances-receiving farm household will have the ability to fund petty trading activities, whereas NGO support to farm households may facilitate access to insurance schemes against climate risk. Given that farmers can adopt different climate change adaptation strategies (CCAS) at the same time, with interdependent decisions (Yu et al. 2020), single-equation models like probit or logit are simply inappropriate since such models fail to capture the interdependencies that exist among different strategies and consequently lead to inefficient and biased estimates due to omitted variable bias or correlated errors across adoption equations (Kassie et al. 2013). An extension of the univariate probit is the Bivariate Probit. While useful for two interdependent choices, it cannot accommodate more than two correlated choices. The next alternative is the multinomial logit/probit models; however, neither MNL nor MNP is suitable since the adoption choices of CCAS were not considered and or perceived to be mutually exclusive. Thus, multinomial logit/probit becomes suitable if a farmer chooses one CCAS from a list of off-farm climate adaptation practices. In this case, the multivariate probit (mvprobit) model was deemed the most appropriate econometric specification to address the setbacks specified above.

Subsequent to the estimation of the multivariate probit which took into account interdependent adoption decisions, our next object of interest was to estimate the effect of off-farm CCAS on farm performance. While we hypothesized that farmers would adopt a combination of strategies in response to climate change, it is important to note that their adoption decision is often self-determined and influenced by observed factors such as household size, education, gender, experience, and membership in farmer-based organization (FBO) (Denkyirah et al. 2017; Mwinkom et al. 2021) and unobserved factors such as skill level and risk preference. In this regard, any attempt to measure causal effect of adoption intensity of off-farm CCAS on farm performance must first take into account the presence of endogeneity due to potential correlation between household intrinsic factors such as the skills, risk bearing, and motivation that could influence both farmers adaptation choices and their farm performance. As Wooldridge (2010) pointed out, if this endogeneity is not addressed, it can lead to bias and inconsistent estimates of the actual impact we seek to determine.

Various scholars in this field have used different models that range from the stochastic frontier model (Ojo & Baiyegunhi 2020) to Endogenous Switching Regression (ESR) model (Suresh et al. 2021; Mogess & Ayen 2023; Adego et al. 2019) to account for endogeneity and sample selection biases and to estimate impact of adaptation on farm output. However, approaches such as stochastic frontier are well suited for technical efficiency analysis. ESR on the other hand, is applicable when adoption decision is treated as binary (adopters vs. non-adopters), and when the researcher's interest lies in estimating counterfactual outcomes under two alternative adoption regimes. Other strands of studies have used the multinomial endogenous switching regression (MESR) model (see Asante et al. 2024) and multivalued treatment effects (MVTE) model (Ma and Zheng 2021) as well as the Multinomial Endogenous Treatment Effect (METE) model (Issahaku et al. 2021) to estimate causal impact. The MESR model, while effective for addressing both observed and unobserved factors, it is not well suited when adaptation is treated as a count measure. Given our principal object of interest was on the number of strategies adopted a count data model will be most appropriate. However, using the Standard Normal Poisson regression would be inappropriate because its assumption of equi-dispersion where the variation of the distribution is equal to the mean would be violated due to potential endogeneity. Indeed, it assumes exogenous explanatory variables. In this reasoning, we favored endogenous exponential mead model over a standard normal Poisson distribution model because it allows for consistent estimation of the causal effect of adaptation intensity while correcting for the presence of endogeneity.

3.4 Econometric (Analytical) Framework

3.4 1 Multivariate Probit (MVPROBIT)

The mvprobit regression was used for the analysis of the adoption of off-farm CCAS with the assumption that a farmer's decision to adopt one CCAS is inherently linked to a different adaptation strategy. The framework for the analysis takes its root from the binary probit model, which assumes that an individual's adoption decision of a CCAS is dichotomous, involving two mutually exclusive alternatives, and is used to determine several correlated binary outcomes of adaptation practices and technology choices. Based on the local context of northern Ghana, we identified four common off-farm CCAS such as livelihood diversification, crop weather insurance, non-governmental organization (NGO) support, and remittances from relatives abroad or elsewhere.

The mvprobit model was ideal because of its ability to establish the relationship between the adoption of different off-farm CCAS while potentially accounting for correlations between the stochastic disturbances (Ahmed 2015). Accordingly, it considers the correlation among the error terms when each of the four off-farm CCAS is modeled individually and evaluates the effects of selected covariates on each of the CCAS simultaneously. As long as the adoption decisions of improved practices are interrelated such that the adoption of one lead to the adoption of another, multivariate could take any number of binary dependent variables. The present study considered a mvprobit model with four distinct binary dependent variables (i.e., livelihood diversification, crop weather insurance and reliance on remittances, and NGO support) estimated in line with Danso-Abbeam & Baiyegunhi (2017), as follows;

$$Y^*_{ik} = \beta_k X_{ik} + a_k A_{ik} + \varepsilon_{ik}; k=1, 2, \dots, 4 \text{ (number of off-farm CCAS)}$$

Where: Y^*_{ik} is the unobserved latent variable representing the propensity of household i to adopt the k th off-farm climate adaptation measure. Thus, it captures both observed and unobserved influences on household adaptation decisions. X_{ik} is defined as a vector of household observed characteristics (i.e., explanatory variables). A_{ik} captures partially observed characteristics of households adopting the k th adaptation measure to account for unobserved heterogeneity. β_k and a_k are the parameters and vectors to be estimated. ε_{ik} denotes the stochastic error term which follows a as the multivariate normal distribution with conditional mean of zero.

The relationship between Y_{ik} and Y^* is given by; 1 if $y^* > 0$, 0 Otherwise. This relationship between observed and unobserved factors as specified above follows the threshold theory of decision-making, where adoption occurs only if the latent utility exceeds a critical threshold. The probability of a household head adopting the k th off-farm CCAS conditional on the explanatory variables was computed using the multivariate normal cumulative distribution function to account for potential correlation between the error terms across the adaptation options. Similarly, we normalized the variance of the joint distributions of the errors to unity such that the random error terms of the adaptation practices are equivalent to the multivariate normal distribution with zero mean and the covariance matrix Z which has the values of 1 on the principal diagonal and a pair-wise correlation coefficient ρ of the error terms with respect to any two estimated adoption equations in the model. The correlation between the error components of different off-farm CCAS is represented by the off-diagonal elements in the Z , as illustrated by Danso-Abbeam & Baiyegunhi (2017), and Azumah et al. (2020). This was based on the assumption that adoption of an off-farm CCAS may depend on a) another CCAS (positive correlation) and b) influence by an available set of substitutes.

3.4 2 Exponential Conditional Mean Model

The exponential conditional mean model (also known as the IV Poisson model) was used to quantify the factors influencing the adoption intensity of off-farm CCAS, as well as its effect on farm performance, among smallholder farmers in northern Ghana. The fact that the outcome variable, farm performance, is a count and non-negative justifies the use of a count data model (i.e., IV poisson). Statisticians and econometricians usually employ the IV Poisson model, which uses additive and multiplicative error terms, to estimate the parameters of a Poisson regression model with some endogenous regressors. The IV Poisson model was ideal because of its ability to estimate the causal impact of adaptation intensity of CCAS on farm performance, and its ability to address the issue of endogeneity. In estimating the model, we explored the two different estimation techniques that have been established in the state-of-the-art to examine the impact of adoption intensity of CCAS and maize productivity of smallholder farmers. The first technique used is the Generalized Method of Moments (GMM) (Cameron & Trivedi 2013; Windmeijer & Santos Silva 1997) and the second approach is by employing a control function estimation (Wooldridge, 2010; 2015). By this approach, as

Wooldridge (Wooldridge 2010) describes, Control Function (CF) estimators assume a certain structural relationship between the endogenous regressors and the exogenous regressors and use functions of first-stage parameter estimates to control for the endogeneity in the second stage unlike the standard generalized methods of moments. As noted above, because the CF approach in the IV Poisson directly corrects for endogeneity bias in the conditional mean outcome, it was used for the analysis.

This structured the framework of our analysis in two-stage procedure. Before the first stage, we computed the adoption intensity of off-farm CCAS from the 412 participants interviewed. The intensity of off-farm climate change adaptation was measured as the number of strategies a farmer adopted which is as specified as follows;

$$\text{Adoption Intensity } (A_i) = \sum_{j=1}^I \text{CCAS}_{ij} \quad \text{-----}1$$

The first level of the analysis involved the determination of the factors that influence the adoption intensity of off-farm CCAS. In this stage, we suspected that farm performance is correlated with unobserved factors that multiplicatively affect adoption intensity of off-farm climate adaptation strategies. So, we treated the adoption intensity of CCAS as an endogenous regressor. Access to climate information was used as an instrument for this variable which was tested for its relevance, thus confirming its validity (see Table 4). The intensity of off-farm CCAS (denoted as A_i) was then regressed on the identified instrument and household exogenous characteristics as follows;

$$A_i = Z_i'\pi + X_i'\delta + \varepsilon_i \quad \text{-----}2$$

Where A_i represent adoption intensity of off-farm CCAS; Z_i' represent instruments (access to climate information) that affect adaptation intensity, and (X_i') being observable household socio-economic characteristics. ε_i (residuals) is a metric for household unobservable factors but are not directly observed. The estimated residuals were then used through control function estimation procedure to correct for endogeneity in the second stage. In this stage, we modelled maize productivity (yield) as a count outcome variable with Poisson distribution conditional on adoption intensity of off-farm CCAS and observed household characteristics.

$$Y_i|A_i, X_i \sim \text{Poisson}(\varepsilon_i) \quad \text{-----}3$$

The conditional mean in the Poisson distribution was specified as;

$$\varepsilon_i = \exp(\beta A_i + X_i'\gamma + \varepsilon_i) \quad \text{-----}4$$

The expected value of maize yield conditional on adoption intensity of off-farm CCAS, household observable characteristics, and error terms is given by the relation below, referred to as the IV Poisson regression with multiplicative errors.

$$Y_i = \exp(\beta_1 A_i' + \beta_2 X_i') \varepsilon_i \quad \text{-----}5$$

To correct for endogeneity, we incorporated the residuals from the first-stage estimation as outlined by Wooldridge (Wooldridge, 2010) to augment the conditional mean specified above. The empirical relation is given below.

$$Y_i = \exp(\beta_1 A_i' + \beta_2 X_i' + v_i' \rho) \quad \text{-----}6$$

Where; Y_i is the maize output of the farm household. β_1 and β_2 measures the effect of the adoption intensity of off-farm CCAS and other selected exogenous variables on maize output, respectively. $v_i' \rho$ are used to

control for endogeneity with the coefficients of ρ (c_extent), as shown in Table 4, measuring the strength of the endogeneity

3.4.3 Variables measurement and descriptions

Table 1: Descriptions of Variables

<i>Variables</i>	<i>Measurement</i>
<i>Multivariate dependent variables: Off-Farm CCA Choices</i>	
Off-farm Livelihood diversification	Dummy; 1 if adopted; 0 for otherwise
Crop weather Insurance	Dummy; 1 if the HH; 0 for otherwise
Remittances	Dummy; 1 if received remittances; 0 for otherwise
Reliance on NGO support	1 if received NGO support; 0 for otherwise)
<i>In Maize yield (outcome variable IV Poisson)</i>	Continuous; Log of yield in kilograms
<i>Household Characteristics and institutional (Explanatory) variables</i>	
Sex	0 if respondent is Female, 1 if Male
Age	Continuous, years
Marital Status	Dummy; 1=married, 0=otherwise
Educational Level	Number of years
Size of the household	Count; Number of people in the household)
Experience of the household head	Continuous; Farming experience in years
wage employment	Dummy; 1 if HH is formally employed, 0 Otherwise
Livestock ownership	Dummy, 1=Yes, 0=Otherwise
Ownership of mobile device	Dummy, 1=Yes, 0=No/Otherwise
Membership in farmer-based organization	Measured as dummy, (0) No (1) Yes
Access to farm credit	Dummy, 1=Yes; 0=Otherwise
Off fam CCAs count (Extent)	Count; Sum of off-farm CCAS
Farm size	Count; Total cultivated land area in acres.
Access to climate information	Dummy; 1 if HH received climate information, 0 for otherwise
PFJ	Dummy; 1 if HH benefited from PFG programme, 0 Otherwise
Road Network	Dummy; (0) poor (1) good
Access to agricultural extension service	Dummy; (0) No (1) Yes
Access to climate smart training	Dummy; (0) No (1) Yes

Source: Authors construct, 2026 Note HH= Household Head

4. Results

4.1 Summary statistics of the respondents

The analyzed sample ($n = 412$) has the following socio-economic characteristics. 17.2% of respondents had access to farm credit, 15.9% had access to climate information, 33% of farmers received climate smart training and 17.3% had access to extension services for their production activities. Most of the respondents, 78.1% ($n=322$), were males with up to 15 years of experience in farming. On average, the total cultivated land area per farmer was 5.8 acres. The average size of the sampled households was relatively large, at eight people per household. While the proportion of household heads with wage employment is low, it was also observed that most of the respondents, 94% ($n=388$) adopted various off-farm climate change adaptation strategies (Table 1). Based on our analysis, 50.8% ($n =209$) of the farmers benefited from the agricultural intervention programs like the Planting for Food and Jobs (PFJ) programme.

Table 2: Descriptive statistics of maize farmers in northern Ghana

Variable	Mean	Std. dev.
Sex	0.708	.4551377
Age	42.654	12.84805
Access to farm credit	.172	.3777584
Livestock ownership	.358	.4798923
Wage employment	.248	.6658699
Experience in maize farming	15.272	12.1638
Household size	7.964	4.580466
Marital status	1.034	.5490418
Access to climate smart training	.33	.4706836
Access to extension service information	.1725768	.3783285
PFG	.508	.5004367
Road network	.74	.6551782
Farm size	5.848577	6.047751
Off-farm CCAs count (Extent)	.942	.9166879
Access to climate information	.1595238	.3666005
Maize yield	7961.041	9164.365

Source: Field data Analysis, 2026

4.2. Determinants of off-farm Climate Change Adaptation

The parametric estimates from the multivariate probit (individual probit models of each of the four CCAS) are presented in Table 2. Variables related to socioeconomic characteristics, as well as institutional membership, are significant in informing off-farm CCAS, including livelihood diversification, crop weather insurance, reliance on remittances, and Non-governmental Organization Support (NGO support). It is

important to note that each of the covariates has a different level of influence on the four outcome variables considered in our multivariate analysis.

In the probit equation for livelihood diversification, we find that access to farm credit, climate information and the size of the farm household as well as sex and age of the household head are less likely to reduce off-farm livelihood diversification. Meanwhile, experience in farming, the size of the farm and the farmer's links with motorable roads were found to be the most influential explanatory variables with significant effects on livelihood diversification. With regard to crop weather insurance, the following variables were found to be influencing determinants that produced significant results for the dependent variable: sex; marital status; educational level of the household head; household size; wage labour (formal employment); participation in agricultural programmes (like the PFG); and access to climate information. However, age; farm experience; household heads with livestock and telephone ownership exerts a negative significant influence on crop weather insurance uptake. In the remittance probit regression model, sex, access to farm credit, livestock ownership, formal employment, farm experience, farm household size, climate smart training, participation in agricultural programmes (like the PFG), and farm size were found to be the most influential determinants (Table 2). In the NGO support probit equation of the multivariate analysis, age, household size, access to farm credit, farm experience of the head, wage labour (formal employment) and livestock ownership, and marital status, access to road network, and participation in agricultural programs (i.e PFG) were predicted as the most influential determinants by the model, yielding significant results, while sex, access to climate information, extension services and climate smart trainings, and farm size produced no significant effect. Regarding the direction of influence, only age, household size, marital status, and access to a good road network had positive relationships on NGO support; the rest had negative relationships.

Across all four dependent outcomes, access to extension service was not found to influence any of the dependent outcomes, while the remaining factors were found to be significant for at least two. Participation in agricultural programs produced only two negative implications for adaptation in the livelihood diversification and remittance model, but showed positive implications for NGO support and crop weather insurance.

Table 3: *Determinants of off-farm Climate Change Adaptation*

VARIABLES	NGO_support	Liv_Diver	Remittance	Crop Weather Insurance
Sex	-0.049 (0.047)	-0.918*** (0.135)	-0.202** (0.0933)	0.108* (0.0643)
Age	0.012*** (0.001)	-0.011*** (0.003)	0.0102*** (0.00227)	-0.00710*** (0.000293)
Farm Credit	-0.747*** (0.084)	-0.338*** (0.0434)	-0.0760** (0.0299)	-0.419 (0.366)
Livestock ownership	-0.628*** (0.0738)	0.0521 (0.0517)	-0.814*** (0.139)	-1.057*** (0.0317)
Wage employment	0.319*** (0.0484)	0.0387 (0.0247)	0.197*** (0.0646)	0.392*** (0.0183)
Experience of farmers	-0.00757*** (0.00232)	0.021*** (0.00467)	0.00761*** (0.00115)	-0.0123** (0.00604)
Household size	0.0148*** (0.00314)	-0.018*** (0.00370)	-0.0337*** (0.00228)	0.0565*** (0.00994)

Marital Status	0.334*** (0.0946)	0.0453 (0.0398)	-0.0427 (0.0315)	0.595*** (0.0122)
Climate Smart Training	0.0317 (0.0548)	0.513*** (0.0225)	0.257*** (0.0749)	0.0148 (0.0753)
Access to extension service	0.00176 (0.153)	0.0794 (0.0967)	-0.105 (0.155)	-0.208 (0.288)
PFG	-0.179*** (0.0566)	-0.111** (0.0502)	0.327*** (0.0598)	0.431*** (0.0510)
Road network	0.539*** (0.0587)	0.235*** (0.0373)	0.0299 (0.0911)	0.378*** (0.0645)
Farm size	0.00435 (0.00860)	0.019*** (0.00520)	0.0323*** (0.00379)	-0.00312 (0.00637)
Climate information	-0.161 (0.190)	-0.450*** (0.0964)	-0.150 (0.237)	0.0972*** (0.0355)
Constant	-1.562*** (0.114)	0.545* (0.300)	-1.441*** (0.179)	-2.856*** (0.186)
atrho21		0.274*** (0.0388)		
atrho31			0.150** (0.0677)	
atrho41				0.347*** (0.0419)
atrho32		0.149*** (0.0279)		
atrho42			0.0244 (0.0542)	
atrho43			0.170*** (0.0541)	
Observations	412	412	412	412

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Likelihood ratio test of rho21 = rho31 = rho41 = rho32 = rho42 = rho43 = 0: chi2(6) = 20.7715 Prob > chi2 = 0.0020

Source: Field data Analysis, 2026

4.3 Effects of Adaptation on farm performance

Table 3 presents the determinants of off-farm CCAS adoption intensity and their effects on maize output. Both the estimated coefficients and incidence rate ratios (IRRs) are reported. Contrary to Issahaku et al. (2021) who established that adoption of multiple climate adaptation strategies leads to higher farmer output, our results show that, conditional on other covariates, a one-unit increase in the intensity of off-farm CCAS adoption is associated with approximately a 15% reduction in expected maize output. Male-headed households have about 5% lower expected maize output relative to female-headed households. Similarly, conditional on adoption intensity, farmers who own livestock have approximately 6% lower expected maize output compared to those without livestock. Each additional year of farming experience increases expected maize output by about 0.3%, while a one-acre increase in farm size raises expected output by roughly 10%. Finally, farmers who received climate-smart training exhibit approximately 7% higher expected maize output relative to those without such training. For adoption intensity, the findings established that male headed households have about 38% lower adoption intensity of off-farm CCAS when compared with female household heads. Also, the results demonstrate that farmers who received farm credit have about 29% lower intensity of off-farm CCAS. The results also demonstrate that farmers who own livestock have about 35% lower adoption intensity compared to farmers without livestock. In line with Ankrah et al. (2024), the model predicted that one additional farm experience increases adoption intensity by approximately 0.5%. Similarly, we find that an increase in household size slightly reduces the intensity of off-farm CCAS adoption. This marks a critical departure from Ankrah et al. (2024) who finds evidence of a positive relationship between household size and climate variability adoption intensity. The findings further suggest that married household heads have about 8% lower adoption intensity of off-farm adaptation strategies compared to unmarried household heads. In addition, farmers who received climate-smart training and those with access to motorable roads have higher adoption intensity by approximately 7.6% and 7.1%, respectively. In parallel with previous work on climate variability adoption intensity (Ankrah et al. 2024), we found that an increase in farm size by one acre slightly lowers adoption intensity of off-farm climate adaptation strategies, while access to climate information, the endogenous regressor instrument for adoption intensity, is associated with about a 22% reduction in adoption intensity

Table 4: Determinants of adoption intensity of off-farm CCAS and its effects on farm performance

<i>Variables</i>	Coefficients		IRR	
	<i>lnoutput</i>	<i>Extent</i>	<i>lnoutput</i>	<i>Extent</i>
Sex	-0.0546*	-0.387***	0.947*	0.679***
	(0.0312)	(0.0279)	(0.03)	(.028)
Age	-6.43e-06	0.00138	1	1.001
	(0.000493)	(0.000854)	(0)	(0.001)
Access to farm credit	0.0149	-0.292***	1.015	0.747***
	(0.0156)	(0.0286)	(.016)	(0.029)
Livestock ownership	-0.0618***	-0.348***	0.940***	0.706***
	(0.021)	(0.0270)	(.019)	(.027)
Formal (wage) employment	0.0270	0.206***	1.027	1.229
	(0.0181)	(0.0141)	(.019)	(.014)

Experience	0.00305*** (0.000866)	0.005** (0.00217)	1.003*** (.001)	1.005** (.002)
Household size	-0.00527 (0.00477)	-0.005 (0.0154)	.995 (.005)	0.995*** (0.015)
Marital status	0.0315*** (0.00667)	0.192*** (0.0154)	1.032*** (0.007)	1.212*** (0.015)
Climate Smart Training	0.0713*** (0.00889)	0.242*** (0.0317)	1.074*** (.01)	0.274*** (0.032)
Access to extension service	-0.0166 (0.0176)	-0.007 (0.136)	.984 (.017)	0.993 (.136)
PFJ	0.0114 (0.0104)	0.0192 (0.0392)	1.011 (.011)	1.019 (.039)
Road network	0.0378 (0.0230)	0.289*** (0.0269)	1.039 (.024)	1.335*** (.027)
Farm size	0.00971*** (0.000653)	0.0128*** (0.00249)	1.01*** (.001)	1.013*** (0.002)
Off-farm CCAS intensity (Extent)	-0.163** (0.0710)		.849** (.06)	
Access to climate information		-0.221** (0.113)		0.802.** (.113)
c_Extent		0.176** (0.0699)		1.192** (.07)
Constant	2.200*** (0.0754)	0.732*** (0.0987)	9.024*** (0.681)	2.079.*** (0.099)
Observations	412	412		

*** $p < .01$, ** $p < .05$, * $p < .1$ $m = 8.531$, Std. dev. = .6603189

Mean dependent var 8.531 SD dependent var 1.029

Source: Field data Analysis, 2026

5. Discussions

The multivariate probit model is a widely adopted measure that accounts for the interrelationship and the independencies of the adoption decision of climate adaptation practices (Bedeke et al. 2019). As our findings show, the adoption of off-farm CCAS is not independent among the sample ($\chi^2 = 20.77$; $p < 0.01$). This means farmers make a joint decision to adopt off-farm CCAS. In the following subsections, we discuss the variables that have significant influence on the off-farm CCAS and describe how adaptation intensity of these practices affect farm performance to advance the state-of-the-art. However, during our discussions, we did not consider the determinants of the adoption intensity of off-farm CCAS due to the similarity of findings with the multivariate probit regression. This consistency between the determinants of off-farm CCAS and adaptation intensity presented here reaffirms the robustness of the socio-economic and institutional factors across the various adaptation scales.

5.1 Determinants of off-farm adaptation strategies

We estimated a mvprobit model to account for the possibility that adoption decisions of off-farm climate change adaptation decisions of smallholder maize farmers in northern Ghana are interrelated and are influenced by unobserved factors common across practices. The multivariate probit estimates presented in Table 2 provide strong empirical support for this joint decision-making framework. The likelihood ratio test of the independence of the error term of the different adaptation equations is statistically significant (at 1% levels). This provides confirmatory evidence to reject the null hypothesis of zero correlation across equations, implying that the adoption decisions for off-farm CCAS among smallholder maize farmers in northern Ghana are not independent. Specifically, the cross-equation correlation coefficient between support from NGO and livelihood diversification was positive and statistically significant (at 1% level), suggesting that unobserved factors that influence NGO support also influence livelihood diversification of farmers. The cross correlation between NGO support for climate adaptation and remittances from immigration and out-migration of farmers' household members was estimated to be positive with statistically significant effect at 5%. This means the unobserved and contextual factors that influence NGO support also influenced remittance from immigration and out-migration. The strong positive correlation between unobserved factors driving NGO support also strongly drive crop insurance adoption (Table 2). Also, the positive significant cross correlation coefficient between livelihood diversification and remittances implies that households receiving remittances from immigration and out-migration are also more likely to diversify their livelihood to mitigate the risk of climate change due to shared unobserved factors. The findings further established a statistically significant positive correlation between remittances and crop insurance implying that farm households that received remittance are more likely to adopt crop weather insurance. This outcome means remittance and crop weather insurance are a perfect complement via unobserved factors rather than viewing them as a single response strategy to the adverse effects of climate change. The above evidence points to the fact that in adverse climatic conditions, farm households may employ a mix of off-farm CCAS leading us to reject the null hypothesis that there is no correlation between the errors of the four off-farm CCAS. The rejection, is therefore in favor of the alternative hypothesis of mutual interdependence (perfect complementarity) among the multiple adaptation strategies of our multivariate analysis due to shared unobserved or contextual factors among possible sets of alternatives. There was, however, no empirical evidence to support the claim that farmers who diversified their livelihood beyond the farm will practice crop weather insurance, indicating some potential trade-offs across the two strategies. The rest of the multivariate probit parametric estimates are discussed below with a specific focus on the direction of individual covariate effects, contrasted with CCAS in the literature, and the dependence structure across adaptation options, which would, otherwise, be obscured under single-equation probit models.

Livelihood diversification was significantly influenced by household demographic and socio-economic characteristics as well as institutional membership and affiliation variables (Table 2). Though the impacts of climate change are not gender neutral as claimed by Adzawla & Baumüller (2021), we found that male-headed households are less likely to engage in off-farm livelihood diversification relative to female headed households (moderate level of significance at 5%). A plausible explanation for this lies in the nature of common off-farm livelihood activities such as petty trading observed in the study area. An off-farm activity such as petty trading is more likely to be observed in female household heads than in male households due to the gendered nature of the activity which is often dominated by women in northern Ghana. Similarly, this finding is consistent with the dominant view and reinforce the widely accepted assertion that female's household heads and female spouses are most vulnerable to the adverse effects of climate change (Adzawla & Baumüller, 2021; Alhassan et al. 2019; Balikoowa et al. 2019). As reported in the Sixth Assessment Report of

the Intergovernmental Panel on Climate Change (IPCC 2022), the economically and socially marginalized groups are most affected by climate change impacts. Their vulnerabilities to climate change could be explained by the fact that women tend to possess fewer assets which are more likely to trigger women participation in livelihood diversification such as petty trading activities so as to strengthen their adaptive capacity. As expected, age of the farm household head was found to have a significant effect on diversified livelihood, which suggest that older farmers are less likely to engage in non-farm business activities (livelihood diversification). This finding is consistent with foundational work by Adamseged & Kebede (2023). One could argue that older household heads have more experience which could facilitate off-farm livelihood diversification. However, our results suggest that this rather potential advantage does not always translate into off-farm livelihood diversification activities like petty trading, likely because diversification requires active labor input rather than experience with climate risk.

Unlike previous studies reporting access to credit to be one of the main drivers that increases farmers on-farm climate adaptation choices (Alhassan 2019; Denkyirah et al. 2017) and off farm livelihood diversification strategies (Haile et al. 2025), our findings established that household head access to farm credit significantly reduces the head's likelihood of participating in off farm activities such as receiving support from NGO programs, receipt of remittance, and engaging in livelihood diversification as mechanisms to cope the inimical impacts of climate. Consistent with Kolog et al. (2024), as in the case of livelihood diversification, this result means that farmers who had accessed to credit are less likely to engage in non-farm business compared to farmers without farm credit, likely because access to farm credit is earmarked for specific purposes and farmers with access to such facility are required to channel the facility for the purpose for which it was obtained. The absence of a positive effect of farm credit on livelihood diversification in our sample, despite strong effects on-farm climate adaptation strategies is probably due to the planned usage of farm credit facility which does not allow farm households to add alternative livelihood activities. Consequently, this makes households who secure credit less likely to diversify beyond agricultural activities. Similarly, as observed, farmers with access to farm credit, relative to farmers without credit facility, are less likely to receive NGO support. A salient point to take into consideration is that most NGO support programs target the marginalized groups and farm households that are most vulnerable in society and are being affected most by worsening impacts of climate change. In this regard, households' heads with access to farm credit may signal greater financial inclusivity or lower vulnerability in the NGO targeting framework. As such, it is not surprising that households with access to farm credit facilities are less likely to be prioritized for NGO support. At the same time, as in the case of remittances, the negative statistically significant relationship could be viewed from the lens that remittances are inflows in response to household needs, implying that household heads with improved access to credit may less likely request for cash from migrant relatives as opposed to those without access to credit facility. This, in turn, will influence household immigrant relatives to adjust cash transfers for household consumption needs and adaptation to the risk of climate change due to the household's ability to access funds.

One of the most evident findings of our analysis is that household wealth and asset indicators such as livestock ownership and farm size are significant determinants of off-farm climate adaptation. While there are some commonalities between these indicators, they remain quite diverse and unique, and the reported effects on off-farm climate adaptation choices between them varies widely. Our findings revealed that farmers who owned livestock have lower chances of receiving NGO support, remittances, and crop weather insurance uptake. This marks a critical departure from the work of prior research that reported asset ownership such as animal increase the probability of adaptation (Issahaku & Abdulai 2020; Shahzad & Abdulai 2020), probably because of subject matter (on-farm vs. off-farm) and raises the question of whether we can consider livestock ownership as an asset-based indicator that enhances off-farm climate adaptation choices. We argue that, given the current body of knowledge that equate asset ownership to increase adaptative capacity, livestock ownerships should not be considered as an additive climate adaptation measure in itself but rather as an exposure risk buffer (Issahaku et al. 2021; Shahzad & Abdulai 2020) that can help households to absorb shocks through sales, reducing the need for external support and reliance on crop weather insurance. This is especially true because households with livestock tend to self-insure (Bwalya et al. 2024; Hänke & Barkmann 2017). There is evidence that farm size had a strong and positive association with off-farm level of climate adaptation strategies such as livelihood diversification and receipt of remittances. One plausible explanation for this is that larger farm size increases the household exposure to climate risk, which may trigger their further engagement in off-farm livelihood diversification. Similarly, large farm size requires more capital that may lead to persistent demands of cash inflows from relatives abroad.

Our results also demonstrate that farmers with access to climate-smart training are more likely to practice off-farm livelihood diversification relative to those who did not receive climate smart training. At the same time,

it increases the likelihood of the farm household dependencies on remittances. These findings are consistent with the dominant view that participation in agricultural capacity-building programs can enhance adoption of Climate Smart Agricultural Practices (CSAPs) (Martey et al. 2021; Zakaria et al. 2020). This is because access to training delivered through extension agents and NGO programs widely increases farmers' awareness of various climate-smart practices that can help reduce the household exposure to production risks and when such training practices are put to use, households can increase agricultural production. An important consideration to note is that utilization of climate smart training is resource demanding, likely raising household dependence on external support from relatives abroad or elsewhere to put such training into practice. Consequently, it is reasonable to suggest that farmers with access to such training have increased chances of diversification due to the reduction in risk of climate change. In addition, we saw, while not statistically significant, the association between farm experience and diversification and likewise NGO support was positive suggesting farmers who have been in production for a very long time have a higher tendency to diversify their livelihoods beyond agricultural production activities.

Results of our study show that motorable roads do not facilitate receipt of remittances. However, access to motorable roads increases household-head (farmers) chances to receive support from non-governmental organizations, engage in off-farm livelihood diversification and crop weather insurances. Most likely because a good road network facilitates better access to banks or insurance institutions and better access to markets which may allow for easy transportation of both agricultural output and non-farm goods to and from the market. This finding provides confirmatory evidence to the state-of-the-art which collectively argued that improved infrastructure facilitates market access and thus encourages farmers to diversify their livelihood (Kolog, 2024). Contrary to what one might expect between NGO support and a good road network, given that civil society organizations serve as bridge in development gaps, the major reason for this observation is simply a matter of access to communities with deplorable road conditions. Finally, our results show that access to climate information may not necessarily translate into off-livelihood diversification, but it increases the chances to practice crop weather insurance.

5.2 Effects of adaption of climate strategies on farm performance

There has been an increasing focus of research in tailored to climate change adaptation and how adaptation of climate smart practices improves farm performance (Issahaku et al. 2021; Issahaku 2020; Shahzad & Abdulai 2020; Bedeke et al. 2019), reduces multidimensional poverty (Issahaku et al. 2021) and enhances household welfare (Shahzad & Abdulai 2021; Martey et al. 2021). In light of these explorations, it emerges crucial to reconsider whether this line of views can be applied to off-farm climate adaptation strategies. This current study empirically investigated the relationships between adoption of off-farm climate adaptation (often viewed as risk buffering activities) and farm performance as a package. Our findings, while uncommon, are counterintuitive but very important for both theory and practice in this field of inquiry.

Many researchers in this field often equate adaptation measures to increased farm performance, at most on the farm level (Issahaku et al. 2021; Bedeke et al. 2019). However, we found strong evidence to suggest that greater adoption intensity of off-farm climate change adaptation strategies do not necessarily increase farm performance. By analyzing a cross sectional data from 412 farmers, we saw that, conditional on other factors, higher adoption intensity is associated with lower expected maize output. With this finding, it is consciously implied that higher adoption intensity of off-farm CCAS should be understood as a rational household risk management response that takes away labor and managerial attention from farming rather than as a mechanism for enhancing productivity. In a similar vein, since both on-and-off-farm climate adaptation strategies vary in purpose and focus, productivity outcomes should not be assumed to be uniformly positive. Although one might argue that adopting several practices could provide household heads with more funds to invest in farm inputs and intensification (see, Mathenge & Tschirley 2008) this finding suggests that combining multiple off-farm CCAS does not always translate to increase farm productivity, which support some concerns that off-farm activities may compete with farm labor (Mathenge & Tschirley 2008). Given these concerns, we can assume that the findings presented in Table 2 are justified based on the following important consideration. However, we believe that there is a need for unified conceptual understanding of the causal impact of the farm performance nexus of off-farm CCAS in other contexts.

First, the pattern we observed is underpinned by conditionality and additionality of a farmer deciding to adopt an extra off-farm climate adaptation strategy. This holds true because, as we have observed, marginal adoption leads to negative expected maize output. This coincides perfectly with diminishing returns to diversification. While limited adoption of off-farm CCAS may relax liquidity against risk, we argue that greater adoption might increase opportunity cost of farm production. Thus, it is not off-farm adoption per se

that reduces expected output, but the marginal uptake of these strategies reduces maize output. The second underlying mechanism that plausibly explain the observed finding is that each additional uptake of off-farm CCAS creates labor time competition (Mathenge & Tschirley 2008) and managerial demands, which in turn, increase the opportunity cost for farm labor, time and managerial oversights for maize production (Saqib et al., 2025). Broadly, our result is consistent with household production theory. Indeed, household models of agricultural production have predicted that under imperfect market conditions off-farm work competes directly with on-farm labor allocation for crop production as seen in previous research (Mathenge & Tschirley 2008; Saqib et al. 2025). In these models, precisely the non-separable model, it is often implied that households make joint decisions about production and consumptions and that households operate larger farms because of labor availability (Singh et al. 1986). Third, adoption of multiple adaptation strategies may increase household transaction costs and stretch managerial capacity, especially where institutional and market access are limited. With this, one would expect that when adaptation choices increase labor will be redistributed to the off-farm.

While the underlying factors explaining the negative association of adoption intensity on expected maize seem to be fairly clear, we can also see that several household observable characteristics conditional on adoption intensity have a very similar effects and somewhat very differing effects on expected maize output which is particularly reflected in the farm size, household size, gender of the household head and livestock ownership. As our findings show, the conditional positive associations of experience and climate-smart training could be due to the very fact that farmers with additional years of farm experience and those who received training could leverage knowledge and skills to partially offset the opportunity costs of off-farm activities, thereby increasing the expected maize output marginally.

Our results further indicate that despite the lower expected output of higher adaptation intensity, farm size has a slight incremental benefit for expected maize yield. Our argument for this is that larger farm sizes allow for some scale effects of expected maize yield of households, however, such benefits may be modulated by adoption intensity of off-farm CCAS, leading to slight positive changes on farm output. With respect to sex, our findings suggest that female farmers tend to have higher expected maize output relative to male farmers. This is especially true because, in the context of northern, and even across the country, females operate small plots of land as compared to men. Due to the smaller size of their landholdings, female farmers are better able to manage their farms more efficiently. Consequently, they turn out to have higher expected maize yield when viewed from the point of per unit land cultivated rather than a holistic view of total farm returns. The finding that the expected output of household heads with livestock's turns to be lower might as well be explained by time, labor and managerial tradeoffs and increased opportunity cost of production, as livestock ownership may interact with adoption decisions to produce heterogeneous outcomes.

6. Conclusions

In this study, we examined whether the causal influence of on-farm climate change adaptation strategies on farm performance, as established in prior research (including the finding that adoption of such strategies improve farm productivity), can be applied in the context of off-farm climate adaptation strategies, by investigating how adoption of off-farm climate adaptation and its impacts on farm performance can be understood. We tested this in a cross-sectional survey of 412 smallholder farmers using exponential conditional mean model and a multivariate probit model. This study rested on the idea that, in their quest to adapt to the increasing exposure to and induced vulnerabilities of the effects of climate change, smallholder farmers often employ a variety of off-farm climate adaptation practices, such as livelihood diversification, NGO support, remittances and crop weather insurance. Compelling evidence was revealed that the choice to adopt these off-farm CCAS is interdependent due to their complementary nature. The joint adaptation decision was determined by household demographics and socio-economic such as (sex, age, marital status, household size, education, experience, and access to good road network), wealth and asset indicators (farm size and livestock ownership) and institutional affiliation variables (access to climate smart training, climate information, and extension service) each with differing effect on the four adaptation outcomes. Additionally, our findings suggest that, conditional on other factors, combining multiple adaptation strategies, including livelihood diversification, NGO support, remittance and crop weather insurance, is expected to reduce maize output. Based on these findings we put forward two key recommendations: (1) Since off-farm CCAS adoption intensity reduces expected maize output, we suggest that efforts to promote off-farm CCAS adoption should be designed with complementary measures such as labor-saving technologies to avoid potential tradeoffs in farm performance; and (2) as we highlight the importance of a central conceptual understanding of the causal impact of the farm performance nexus of off-farm CCAS, we suggest future climate adaptation research to extend this study to other off-farm level adaptation and in other context, to improve on the

nuances we established. These recommendations aim to guide future research towards more precise understanding of how off-farm CCAS influences farm performance, ultimately contributing to a clearer and more cohesive body of knowledge in the field. These recommendations aim to direct future research towards a more accurate understanding of how off-farm CCAS affects farm performance, thus enhancing the clarity and coherence of the knowledge base in this domain.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Artificial Intelligence

During the writing of this manuscript, the authors used Grammarly to check the spelling and grammar, and DeepL to enhance the wording of the text. All enhanced text was subsequently reviewed and edited as necessary. We take full responsibility for the content of the publication.

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