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Mintewab Bezabih, Byela Tibesigwa, and Martine Visser

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The Adoption of Climate-Smart Practices and its Impact on Farm Income: The Case of Arid Namibia

Mintewab Bezabih, Byela Tibesigwa, and Martine Visser*

Abstract

This study assesses the adoption of climate smart agricultural practices in arid Namibia and their impact on agricultural income. The estimation relies on multinomial endogenous switching regression estimations so as to account for simultaneous availability of multiple adaptation technologies, heterogeneity in adaptation, and possible selection bias in adoption. The analysis focused on comparing the impact on farm (crop and livestock) revenues of alternative adaptation technologies. Comparison of the relative importance of alternative adaptation practices shows that adaptation, all in all, leads to gains in farm income. We also found interesting results from singular versus combination adoption, with the former having higher impact on income as the number of diverse activities increases. This finding suggests that, given the diverse nature of Namibian agriculture, adoption of cross-sectoral practices is not always beneficial.

Keywords: climate-smart agriculture, combination of strategies, dryland smallholder farm household farm income, multinomial endogenous switching regression, Namibia

JEL Codes: Q5, Q15, D14

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* Mintewab Bezabih (corresponding author: mintewab.ayele@gmail.com), Environment and Climate Research Center, Policy Studies Institute, Addis Ababa, Ethiopia. Byela Tibesigwa, University of Dar es Salaam, Tanzania. Martine Visser, Environmental-Economics Policy Research Unit, University of Cape Town, South Africa. The authors gratefully acknowledge funding from the Swedish International Development Cooperation Agency (Sida) through the Environment for Development Initiative at the University of Gothenburg.

1. Introduction

The 2018 Intergovernmental Panel on Climate Change (IPCC) report states that dryland agriculture in sub-Saharan Africa is likely to continue to suffer the impacts of continued global warming. Despite this, previous international agreements have generally failed to fully engage developing countries (Cao, 2010) partly due to their emphasis on mitigation and not adaptation. The 2015 Paris Agreement places unprecedented importance on actions needed to help people adapt to a warmer world, and solidifies expectations that all countries will do their part to promote greater climate resilience. In particular, an aspect of the agreement which requires submission of the Nationally Determined Contributions by governments enables identifying the adaptation options associated with several activities (Davide et al., 2018). Hence, for developing countries, there is, inter alia, a need to generate sufficient quantitative information on impact and feasibility of adaptation options.

Several studies have documented that the economic impacts of climate change on agriculture can be significantly reduced through adaptation practices (Kurukulasuriya and Mendelsohn, 2006; Mano and Nhemachena, 2006). Both the general literature (such as Wang et al., 2010) and specific studies in Africa have focused on factors that affect the choice of a single practice (Deressa et al., 2010; Di Falco et al., 2012). However, adaptation practices are rarely undertaken in isolation and farmers typically adopt several adaptation practices at a time on their fields.

Despite this, studies that take into account this critical feature of multiple adaptation remain limited. Recently, however, studies that feature multiple adaptation as their central theme are mounting. These include studies from Ethiopia (Teklewold et al., 2017; Veronesi and Di Falco 2015) and Malawi (Asfaw et al., 2016; Kassie et al., 2015). This paper follows suit in evaluating farm returns due to adoption of a combination of climate-smart adaptation practices under changing climate conditions.

The analysis in this paper, however, makes an important departure from these studies in the following three ways. First, by comparing alternative adaptation strategies, it unearths whether the relative contribution of the adaptation strategies changes when used in combination or not. Second, the paper assesses the impact of water-smart technologies in enhancing farm level revenue by comparing them with other adaptation technologies. The emphasis stems from the water-constrained and largely arid nature of Namibian agriculture. Third, as previously described, similar studies are from Eastern Africa. Therefore, a study that is based on data from Namibia will generate much needed systematic information on adaptation potentials from elsewhere in Africa – particularly Southern Africa.

Note that our study is closely related to a study by Gitonga and Visser (2018) which investigated the association between climate information and adaptation practices using the same data set that is employed in this paper. Unlike Gitonga and Visser (2018), we focus on multiple adaptation technologies and our emphasis is on the returns to adaptation and not on the role of climate-smart information. The choice of methodology, as in Di Falco and Veronesi (2014) and Teklewold et al. (2017), accounts for the following: simultaneous availability of multiple adaptation technologies, heterogeneity in adaptation and possible selection bias in the adoption of climate adaptation technologies. However, in contrast to Di Falco and Veronesi (2014) and Teklewold et al (2017), our focus is on a combination of adaptation practices.

The issue is of essence to Namibia for the following reasons. First, agriculture is one of the main economic activities in Namibia contributing 3.7% of GDP (Davies et al. 2019), with more than 70% of its population relying on agriculture (Taapopi et al. 2018). The majority of the farms involve smallholder agriculture, and often subsistence farming (Halle and Bruzon 2007; Davies et al. 2019), which implies that households engage in farming mainly to generate food for the households. As a way of improving farmers' resilience and up-scaling climate change strategies, in 2015 the government developed a draft national climate-smart agriculture programme, but the adoption has been slow (Davies et al. 2019). Second, Namibia is already naturally sensitive, as it is one of the driest countries in the region, where 92% of the land is considered as hyper-arid, arid, or semi-arid, due to low rainfall and high temperature (Halle and Bruzon 2007; Taapopi et al. 2018). The country has a single wet season, with low, highly variable and unpredictable rainfall, where the average annual rainfall is about 350mm; all this is accompanied by high temperatures. As a result, Namibia is extremely vulnerable to climate change, water stress and land degradation, with water scarcity being a major obstacle to food security and development (Halle and Bruzon 2007).

The analysis uses a cross-sectional farm data set collected from a random sample of households who engage in smallholder farming in Namibia. Methodologically, identification of the average adoption effect is based on a multinomial switching regression method to account for simultaneous multiple adaptation technologies, heterogeneity in adaptation and likely selection bias. We additionally control for various household and plot-level characteristics.

The results show that the adoption of any of the climate-smart practices increases agricultural revenue. Our analysis of paired adaptation indicates that crop-based adaptation outperforms other adaptation practices; water-smart practices alone were found to be inferior in terms of increasing household income (crop and livestock). Despite common wisdom that arid agriculture gains from adoption of water-smart practices, the implication of the results is that water-smart adaptation works better in combination with other climate-smart practices. We further observe that receiving timely climate information is positively and significantly related to the adoption of these practices.

The rest of the paper is organized as follows. In section 2, a literature review is presented that links climate and water-smart agriculture and agricultural productivity. Section 3 describes variables and data employed in the analysis, along with the different data sources. The econometric methodology is presented in Section 4. Section 5 discusses the empirical findings and Section 6 concludes the paper.

2. Climate-Smart Agricultural Practices and Farm Income: A Literature Review and Hypotheses

Climate change is increasingly becoming one of the most formidable challenges to economic development (Skoufias, 2012). For smallholder farmers in Africa, the vagaries of climate change exacerbate an already vicious circle of poverty and environmental degradation (Mendelsohn and Dinar, 2009; Deressa et al., 2009).

In this literature review, we take into consideration the following five adaptation decisions in our empirical analysis, based on the Namibian setting. The first category is agricultural water management as an adaptation strategy. While of undisputed importance, it has received little attention in the literature so far. The reduction in water availability as a result of climate change (both in terms of quantity and reliability) increases the need for an efficient water management system for agriculture, particularly in Africa (Vörösmarty et al. 2010). The responsiveness of irrigated and rainfed farms to climatic factors is shown to be significantly different in Africa (e.g., Deressa et al. 2006), South America (Seo and Mendelsohn 2008), and the U.S. (Wanga et al. 2009). Irrigation's role in adaptation is attributed to shielding farmlands from sensitivity to precipitation and compensating for higher temperatures (Ariel and Dinar, 2003). Similarly, in a study of seven Latin American cases, (Seo, 2011) finds that public irrigation does not increase in response to a warmer climate, but private irrigation does. However, irrigation's effectiveness will be affected by changes in the reliability and quality of those diminishing water supplies (Eliotta et al., 201; Connor et al., 2012). In their study of drought response in China (Chen et al., 2013) showed that a significant number of farmers used engineering-based water management practices to increase the amount of irrigation water and to improve the reliability of the water used in irrigation, including wells to access groundwater resources, cisterns to collect rainfall, pumps to draw water from a nearby river or lake for irrigation, surface pipe or sprinkler irrigation facilities to improve their drought adaptation ability, and maintaining canals to reduce canal water leakage and water delivery losses. In terms of the impact of adaptation, we focus on farm-level productivity. This is because one key channel through which climate affects farmers' livelihood of farmers is through significant yield reduction (Masseti and Mendelsohn, 2011; Deschenes and Greenstone, 2007)[1]. This

[1] Eliotta et al. (2011) show that, for Africa, the impact of climate change on crop yields is largely negative, with declines up to 24% estimated at the end of the 21st century.

effect exacerbates already existing low productivity for which low adoption of farm technologies is identified as a key factor (Kassie et al., 2012).

The second adaptation category is land- and soil-based adaptation. Technologies such as the use of soil and water conservation methods/technologies and conservation agriculture (minimum tillage, mulching, etc.) are also considered. This strategy has been credited as a pivotal instrument of climate change adaptation, particularly in Africa (Di Falco and Veronesi 2014; Teklewold et al. 2015; Deressa et al. 2009; Di Falco and Bulte 2011; Kato et al. 2009). The third category, crop-based adaptation, includes any crop-related alteration to farming, including changing harvesting or planting times, increasing the area cultivated to grow more crops (extensive cultivation), having plots in different geographical areas, or shifting planting of crops to different/more suitable locations. It also includes introducing new crop varieties that have not been grown before, adopting early maturing varieties to escape drought, sequential timing of cropping, and adopting drought-tolerant varieties. In line with this, a number of studies support the viability of alternative crop-altering strategies as adaptation strategies (Deressa et al., 2009; Kurukulasuriya and Mendelsohn, 2008; Hassan and Nhemachena, 2008). Diversification into new kinds of crops is known to reduce the risk of crop loss associated with climatic variability (Di Falco et al. 2010; Di Falco and Chavas 2009). Equally important are particular seed varieties that are naturally drought-tolerant or are developed for drought tolerance, which play an effective role in buffering against drought (e.g., Bezu et al., 2014).

The fourth category includes changing livestock from large to small ruminants. Changing livestock composition – particularly moving from dairy and beef cattle to sheep and goats – can be considered an effective adaptation strategy (Seo and Mendelsohn, 2008). Other adaptation options in the region include moving livestock to other geographical areas, purchase more of the same type of animals, livestock sale/destocking, obtaining goat grazing rights from traditional authorities, and using supplementary feeding.

3. Description of the Study Area, Data and Variables

3.1 The Study Area and Data

Data consists of information gathered from a random survey of 654 Namibian rural households conducted in 2017, as part of the Adaptation at Scale in Semi-Arid Regions (ASSAR) project. The sampling strategy followed a stratified random sampling design, with the first stage involving purposively selecting the three regions in Northern Namibian, namely, Omusati, Oshana, and Oshakati. This was followed by choosing two districts each from Oshana and Oshakati, and three districts from Omusati. The choice of the regions and subsequently the districts within them is meant to reflect diversity in climate and agricultural productivity.

Random sampling proportionate to size was then used to select villages and households to include in the survey.

The data gathered consists of information on households' socioeconomic background, household composition, agricultural practices, household food security, adaptation and other coping strategies. Climate in the region is semi-arid, and rainfall is erratic both in quantity and timing. Two constituencies were each selected from Oshana, and Oshakati and three from Omusati to capture diversity within the regions. The agricultural system in the study area is dominated by livestock production in combination with small-scale cereal production. Crops are grown on individual farms, while livestock are herded on communal grazing lands, which are the major sources of animal feed. The crop production system consists of sorghum, millet, bamboo, vegetables and legumes. Supplemental sources of livelihood include *mopane* worm production, timber and non-timber production, off-farm income activities and participation in government transfer programs.

3.2 Dependent and Explanatory Variables

Below we discuss the key dependent and explanatory variables used in the analysis.

3.2.1. Dependent Variables

The main dependent variable, farm income, is the total of crop and livestock revenue reported in the survey. Crop revenue is calculated from the sum total of value of each crop by household. The livestock revenue is obtained from the response to the question "What is the total value of livestock received in the last 12 months?"

Climate-Smart Adaptation Strategies

Regarding adaptation strategies, the households were asked about adaptation options that they might have adopted over the last ten years. Respondent households are identified as adopters if they responded 'yes' to the following question 'Have you tried any adaptation strategies in the past 10 years?'

Because the main focus of this paper is to investigate alternative benefits of individual versus joint adoption of adaptation technologies, we construct variables that capture cross-sectoral adaptations and interactions. Specifically, we categorize the adaptation strategies, including crop, livestock, and water type strategies. Although 41 adaptation types are identified in the survey, we considered only 12 strategies, as considering all 41 strategies would have meant there would have been no reference/no adaptation category. Below, we discuss the adaptation strategies considered in this analysis.

The *crop-related category* includes adopting drought-tolerant crop varieties, sequential timing of cropping (e.g., planting different portions of land at different times during a season), early-maturing crops to avoid the effects of drought, and using conservation agriculture (minimum tillage, mulching, etc.). *Livestock-related adaptation* includes supplementary feeding (stored hay, buying feed, feeding crop residues to animals), changing the composition of livestock herds and/or purchasing new types of animals (e.g., shifting from cattle to goats/sheep and camels), livestock sale/destocking, moving livestock to other geographical areas, and purchase of new types of the same animals (e.g., cattle that are more productive or drought resistant). Also included as a strategy is *water-related adaptation*, where we consider using rainwater harvesting (infield pits and follows), the use of earth dams, drip irrigation, and rehabilitation of natural water points as water accessing and adaptation mechanisms. Table 1a presents the adaptation categories.

In our analysis, the singular adaptations represent one of these three categories i.e., a household only adopts one strategy, regardless of category. That is, adoption of only one of the strategies in any of the three categories is identified as singular adaptation. Those who have adopted one of the strategies (but not a combination of them) form 30 percent of our sample. In terms of combinations, four different categorizations can be conceived. The first combination we consider is the crop-livestock combination. The second combination is crop-water combination and the third combination the livestock-water combination. The fourth combination of adaptation strategies is from the three sectors simultaneously: crop, livestock, and water. This “combination” category represents a total of 34 percent of the households. The rest of the households form around 35 percent of the households and we use them as the baseline/ reference categories for the econometric analysis. Table 1b presents adaptation categories based on crop/livestock/water adaptation and those are considered in the econometric analysis.

Table 1a: Adaptation options considered in the analysis of a combination of crop, livestock, and water-based strategies (climate-smart technologies)

category	Adaptation categories	mean	Std.Dev.
crop_based			
	Adopted dry tolerant crops variety(ies)	0.723	0.448
	Sequential timings of cropping (e.g. planting different portions of land at different times in season)	0.723	0.448
	Adopted early maturing crops (drought escaping)/changing	0.691	0.463
	Started using conservation agriculture (min. tillage, mulching, etc)	0.147	0.355
livestock_based			
	Used supplementary feeding (stored hay, buying feeds, crop residues)	0.108	0.311
	Changing the composition of livestock herds. Purchase of new types of animals (e.g. shifting from cattle to goats/sheep and camels)	0.093	0.291
	Livestock sale / destocking	0.274	0.446

Moving livestock to other geographical areas	0.142	0.349
Purchase of new types of the same animals (e.g. cattle that are more productive or drought resistant)	0.028	0.165
water-based		
Started using rainwater harvesting (infield pits & follows) and household	0.004	0.061
Started using drip irrigation	0.531	0.500
Used earth dams	0.531	0.500
Rehabilitation of natural water points	0.406	0.492

Table 1b: Adaptation options considered in the analysis of a combination of crop, livestock, and water-based strategies (climate-smart technologies)

Climate-smart adaptation		
	Freq.	Percent
crop/livestock/water adaptation	163	30.35
a combination of either of the crop/livestock/water adaptation	184	34.26
Other adaptation/reference category	190	35.38

3.2.2. Explanatory Variables

Table 2 presents a number of household and farm-level characteristics as controls. These include the head of the household's age, gender, education and occupation. Household size and assets also are considered. Farm-level characteristics include fertilizer, seeds and type of soil.

Around 46 percent of the surveyed households have a female head. The average age of the household head is 62. The proportion of household heads who are able to read and write is 42 percent. An average household has around six family members. Livestock ownership, measured in tropical livestock units, is around six per household.

The average proportion of fertile plots per household is 50 percent, while the average number of plots within the household is 1.1.

Three variables represent climatic shocks in our study: crop, livestock, and water related. To establish crop-related climate shock, our study utilizes information collected from the survey regarding whether a household has experienced crop losses related to drought in the past. Similarly, to construct the livestock and water related climatic variables, survey information on incidences of exposure to livestock losses associated with drought and water reduction were used. Based on this, about 67% have experience of some form of climatic shocks in the past.

The average number of households with family/relatives living outside of the villages is 6 on average.

Table 2: Descriptive statistics of explanatory variables used in the analysis

Variable	Mean	Std. Dev.
Socioeconomic Characteristics		
Age of the household head	62.01701	17.08994
Gender of the household head	0.460674	0.498918
Training of the household head	1.428839	1.465549
Marital status of the household head	2.734082	1.753174
Family size	5.6946	3.115295
Physical farm characteristics		
Number of plots	1.100746	0.319344
Access to fertile plots	0.513967	0.500271
Quantity of fertilizer used	7.100559	89.82037
Quantity of seeds used	9.556797	114.1024
Number of livestock owned (in Tropical Livestock Units)	6.531862	15.96277
Previous experiences		
previous experience of reduced yield	0.743017	0.437378
cropping season	0.351955	0.478025
Climatic variables		
crop related climatic exposure	0.275605	0.447235
livestock related climatic exposure	0.530726	0.49952
water related climatic exposure	0.594041	0.491535
Instrumental variables		
Previous experience of climatic shocks	0.674116	0.469141
Family/relative of the household outside of the village	5.81378	6.799278
Dependent variable		
farm income	6057.078	15446.94

4. Empirical Methodology

Our analysis of the effect of climate-smart agricultural technology on household farm income, conditioned by climate information, involves comparing the impact of technology on agricultural production of smallholder farm households. We assume that farmers make adoption decisions based on expected benefits. However, the decision to adopt the technologies is based on individual self-selection. That is to say, farmers who adopted a given technology may have systematically different characteristics from the farmers who chose another technology or did not adopt any such technology. Quantifying this relationship using ordinary least squares estimation may lead to unobservable characteristics of farmers and their farm affecting both the adoption decision and agricultural income, and resulting in inconsistent estimates of the effect of adaptation technologies on farm income. Hence, accounting for the possible endogeneity of the adoption decisions on farm income becomes imperative.

Because the farmers are faced with a multitude of choices of technologies to adopt, we set out to estimate multinomial endogenous switching, similarly to Di Falco and Veronesi (2014) and Teklewold et al. (2017). For this, we specify a model of adaptation and farm revenues in a two-stage framework. The first stage specifies the choice of mutually exclusive adaptation technologies in response to climatic variables. The second stage outlines an econometric model that is used to investigate the effects of adaptation strategies on net revenues.

The first stage estimation: adoption of climate-smart technologies

The farmer deciding on the adoption of one or more climate-smart agricultural technologies will be faced with a choice of individual or combinations of the available practices. The multinomial logit approach will be the appropriate econometric approach to model such a decision process.

Mathematically, for a vector of interventions $j(j = 1, \ldots, J),$, the farmer i maximizes the expected utility function given by W_{ij}:

$$W_{ij} = K_i\alpha + u_{ij} \tag{1}$$

where K_i is observed exogenous variables affecting adaptation; u represents unobserved characteristics that capture an individual's propensity to adopt; and α stands for a vector of parameters to be recovered in the first stage estimation.

The farmer's utility from choosing a combination of climate-smart practices, W_{ij}, is not observable, but the choice is. The decision rule is that farmer i chooses a combination of technologies j if K_{ij}^* gives him the maximum possible utility. This implies that the farmer will choose the combination of adaptation practices, j, in preference to adopting any other combination of practices, s, if

$$W = \begin{cases} 1 \; iff \; W_{i1}^* > \max\limits_{s \neq 1} W_{is}^* or \; \gamma_{i1} < 0 \\ \quad\quad\quad\quad \vdots & for \; all \; s \neq j \\ J \; iff \; W_{ij}^* > \max\limits_{s \neq j} W_{is}^* or \; \gamma_{ij} < 0 \end{cases} \tag{2}$$

Equation (2) implies that the i^{th} farmer will adopt a combination of practices to maximize his expected farm income if it provides greater expected farm income than any other package that is, if $\gamma_{ij} = \max\limits_{s \neq j}\left(W_{is}^* - W_{ij}^*\right) < 0$.

As per equation (1) , it is assumed that the covariate vector K_i is uncorrelated with the idiosyncratic unobserved stochastic component e_{ij} . Under the assumption that e_{ij} are independent and identically Gumbel distributed (that is under the Independence of Irrelevant

Alternatives (IIA) hypothesis), selection model (2) leads to a multinomial logit model (McFadden 1973) where the probability of choosing strategy j (P_{ij}) is

$$P_{ij} = Pr(\gamma_{i1} < 0|K_i) = \frac{\exp(K_i\alpha_j)}{\sum_{s=1}^{j}\exp(K_i\alpha_s)} \tag{3}$$

The Second Stage Estimation: The Effect of Adaptation on Farm Income

In the second stage, we model the effect of climate-smart agriculture on household farm income via a representation of the production technology by applying Bourguignon, Fournier, and Gurgand's (2007) selection bias correction model. Our model implies that farm households face a total of M regimes (one regime per strategy, where j =1 is the reference category "non-adopting").

The conditional Ricardian specification for each possible regime is given by:

$$W = \begin{cases} Regime\ 1\text{:}\ R_{i1} = M_i\vartheta_1 + \varepsilon_{i1}\ if\ I = 1 \\ \qquad\qquad\qquad . \\ \qquad\qquad\qquad . \qquad\qquad\qquad for\ all\ s \neq j \\ \qquad\qquad\qquad . \\ Regime\ s\text{:}\ R_{is} = M_i\vartheta_s + \varepsilon_{is}\ if\ I = s \end{cases} \tag{4}$$

where $R_{ij}^{\prime s}$ are the outcome variables of the i^{th} farmer in regime j and the error terms $\varepsilon_{ij}^{\prime s}$ are distributed with $\mathrm{E}(\varepsilon_{ij}|K,M) = 0$ and $\mathrm{Var}(\varepsilon_{ij}|K,M) = \delta^2$. R_{ij} is observed if and only if combination of climate-smart practices j is used , which occurs when $W_{ij}^* > \max_{s\neq j}(W_{is}^*)$. If the $e_{ij}^{\prime s}$ and $\varepsilon_{ij}^{\prime s}$ are not independent, a consistent estimation of ϑ_j requires inclusion of the selection correction terms of the alternative choices in (3). Bourguignon et al. (2007) show that consistent estimates in the outcome equations (3) can be obtained by estimating the following selection bias-corrected net farm income:

$$U = \begin{cases} Regime\ 1\text{:}\ R_{i1} = M_i\vartheta_1 + \delta_{1\eta}\pi_{1i} + \omega_1 ifU = 1 \\ \qquad\qquad\qquad . \\ \qquad\qquad\qquad . \qquad\qquad\qquad for\ all\ s \neq j \\ \qquad\qquad\qquad . \\ Regime\ m\text{:}\ R_{is} = M_i\vartheta_s + \delta_{s\eta}\pi_{si} + \omega_1 if\ U = s \end{cases} \tag{5}$$

where δ_j is the covariance between $e_{ij}^{\prime s}$ and $\varepsilon_{ij}^{\prime s}$ and $\pi_j$is the inverse Mills ratio computed from the estimated probabilities in (3) as follows:

$\pi_j = \sum_{s=1}^{j} \rho_j \left[\frac{\hat{P}_{is}(\ln(\hat{P}_{is}))}{1-\hat{P}_{is}} + \hat{P}_{ij}\right]$, ρ_j is the correlation coefficient of $e_{ij}^{\prime s}$ and $\varepsilon_{ij}^{\prime s}$ are error terms with an expected value of zero. In the multinomial choice setting, there are J-1 selection correction terms, one for each alternative combination of adaptation practices.

It should be noted that for the model to be identified, it is important to use as exclusion restrictions – thus as selection instruments – not only instruments automatically generated by the nonlinearity of the multinomial logit selection model, but also other variables that directly affect the selection variables (adaptation) but not the outcome variable (agricultural income). For this purpose, we follow Di Falco et al. (2014) in choosing previous experience of climate-related shocks as one of the instruments. In addition, we use the number of family members/relatives living outside the village as additional selection variables. This is based on the premise that such connections could carry information about technology adoption. However, such information is not expected to have any direct impact on agricultural income, which is directly dependent on the actual inputs used in production.

Following Di Falco, Veronesi and Yesuf (2011), the admissibility of these instruments is established by conducting a falsification test. The test is conducted by including these variables as regressors on the selection and outcome equations separately in order to test the assumption that the instrumental variables affect the technology adoption decision but do not influence the agricultural income outcome. We find that selection instruments significantly affect the decision of choosing an adaptation strategy but do not affect the agricultural income. The falsification test result is presented in Appendix B2. Table B of the appendix show that access to government support and remittances can be considered as valid selection instruments: they are jointly statistically significant drivers of the decision to adopt a strategy but not of the farm income of the farm households that did not adopt.

Conditional Expectations and Treatment Effects

In this section, we show how to estimate the average adoption effect of a singular/ combination of agri/forest-based interventions from the econometric approach outlined above. There are three post-estimation parameters that are most commonly of interest. The first is the average adoption effect on the population (ATE). This is the unconditional average adoption effect, which answers the question of how, on average, the net farm income would change if everyone in the population of interest had been "treated" with a particular combination of adaptation practices, relative to none of them adopting any practices. The second is the average adoption effect on the adopter (ATT). This is the average change in the outcome variable for adopters as a result of receiving the treatment. The third is the average treatment effect on the non-adopter (ATU), under the counterfactual situation where everyone who did not adopt had in fact received the treatment.

The ATE of combination of practices (j) versus package (1) is defined from equation (6) as:

$$ATE = E\left(R_{ij} - R_{1i} \middle| M = m_i\right) = M_i(\vartheta_i - \vartheta_j) \qquad \text{for } j = 1,2,\dots,s \qquad (7)$$

In observational studies, where the investigators have no control over the assignment of the package of adaptation practices, the adoption status is likely to be dependent on outcomes and thus a biased estimator of the ATE. However, the ATT and ATU are used to compare expected net farm income of adopters and non-adopters with the counterfactual hypothetical case that adopters did not adopt and vice versa. Following Carter and Milon (2005), the expected net farm income under the actual and counterfactual hypothetical cases are computed as follows, by applying Equation (6).

Adopters with adoption (actual): $E\left(R_{ij} \middle| I = j\right) = M_{ij}\vartheta_j + \vartheta_j\lambda_{ij}$ (8)

Non-adopters without adoption (actual)$E\left(R_{1j} \middle| I = 1\right) = M_{1j}\vartheta_j + \vartheta_j\lambda_{1j}$ (9)

Adopters had they decided not to adopt (counterfactual): $E(R_{i1}|I = j) = M_{ij}\vartheta_1 + \sigma_1\lambda_{ij}$ (10)

Non-adopters had they decided to adopt (counterfactual): $E\left(R_{ij} \middle| I = 1\right) = M_{ij}\alpha_j + \sigma_j\lambda_{i1}$ (11)

These expected values are used to compute unbiased estimates of the effects of adoption on adopters and on non-adopters. The average climate-smart practices adoption effect on the adopters (ATT) is defined as the difference between Equations (8) and (10):

$$ATT = E\left(R_{ij} \middle| I = j\right) - E(R_{i1}|I = j) = M_i\left(\vartheta_j - \vartheta_1\right) + \lambda_{ij}\left(\sigma_j - \sigma_1\right) \text{for } j = 1,2,\dots,s \qquad (12)$$

Similarly, the average effects of adoption of a combination of climate-smart practices on non-adopters (ATU), i.e., the counterfactual effects of adoption on those who did not adopt if they had adopted, is computed as the difference between Equations (10) and (12):

$$ATU = E\left(R_{ij} \middle| I = 1\right) - E(R_{i1}|I = 1) = Z_i\left(\vartheta_j - \vartheta_1\right) + \lambda_{ij}\left(\sigma_j - \sigma_1\right) \text{for } j = 1,2,\dots,8 \qquad (13)$$

5. Results

This section presents estimation results from the two stages of the multinomial switching regression, followed by the treatment effect estimations. Accordingly, we first present and discuss the first stage multinomial endogenous switching regression results based on equations (3) and (4). Similarly, the treatment effect estimations are presented based on the estimations in equations (11) and (12).

5.1 Results from the Multinomial Switching Regression: Selection Equation / First Stage Estimation

Table 3 shows the estimation results from the first stage of the multinomial logit switching regression model based on combination of crop/livestock/water categories. The results indicate that age and gender have no significant impact on adoption in any of the categories. By contrast, training increases the likelihood of adoption of a combination of adaptation practices. Marital status of the household head is a negative determinant of singular adaptation categories (i.e., a household only adopts one strategy, regardless of category), but has no significant impact on the likelihood of adaptation of the combination of adaptation categories (i.e., a household adopts more than one strategy, regardless of category). Family size is a negative determinant of adaptation – both singular and combined.

Of the physical farm characteristics, all the determinants have insignificant impact on adoption in any of the categories.

The climatic covariates negatively and significantly affect the adoption of both singular and combination of adaptation strategies. This is particularly the case for crop and water related the climatic variables. While the statistical significance of these of climatic variables on the probability of adaptation can provide some evidence that the adaptation strategies undertaken by farmers are indeed correlated with climate, the positive coefficients run contrary to expectations that experience with climatic shocks reduces the probability of adoption.

Being a recipient of government support displays a positive impact on some strategies. This indicates the positive correlation between government support and access to information regarding climate change and adaptation. However, timely remittance is a negative and significant determinant of adaptation in the singular adoption category.

Table 3: Selection Equation-Multinomial Endogenous Switching Regression of combination of crop/livestock/water adaptation

	single adaptation strategy	combined adaptation strategy
Age of the household head	-0.013+	0.003
	(-1.79)	(0.45)
Gender of the household head	-0.439	-0.549*
	(-1.58)	(-2.20)
Training of the household head	0.073	0.091
	(0.85)	(1.22)
Marital status of the household head	-0.199*	-0.166*
	(-2.50)	(-2.33)
Family size	-0.145**	-0.061+
	(-3.23)	(-1.77)
Number of plots	0.918*	-0.412
	(2.54)	(-1.04)
Access to fertile plots	-0.922***	0.115
	(-3.62)	(0.52)
Quantity of fertilizer used	-0.001	0.001
	(-0.36)	(0.46)
Quantity of seeds used	0.003	-0.002
	(1.09)	(-0.57)
Number of livestock owned (in Tropical Livestock Units)	0.020	-0.023
	(1.56)	(-1.43)
cropping season	-0.617*	-0.758***
	(-2.37)	(-3.31)
previous experience of reduced yield	0.552+	0.653*
	(1.86)	(2.50)
crop related climatic exposure	-0.126	-0.562*
	(-0.46)	(-2.39)
livestock related climatic exposure	0.025	-0.023
	(1.40)	(-1.31)
_cons	0.760	1.440*
	(0.99)	(2.02)
Wald test on instrumental variables ($\chi 2$)	8.03	
	0.0454	
F	104.38	
N	0	
N	537	
t statistics in parentheses		
="+ p<0.10	* p<0.05	* p<0.05

5.2 Treatment Effects

The multinomial endogenous switching regression model can be used to compare observed and counterfactual farm revenues conditional on alternative climate-smart adaptations. Table 4 compares the expected farm revenues of households that adopted a combination of climate -smart practices versus those who did not.

The decision to adopt one of the three (crop, livestock, and water conservation) adaptation practices will lead to a gain of NAD[2] 2334.6 in net farm revenue compared to the decision not to adopt the technology by the same set of households. This gain is calculated as the difference between the net revenue of adopting households who adopted (NAD 4866) and the same set of adopting households if they did not adopt (NAD 2903). The t-test shows significance, indicating that the difference is statistically significant. We then compared the farm income for households that adopted a combination of one of the three adaptation categories (crop and livestock, crop and water, livestock and water) or all three adaptation categories with the counterfactual of the adopting households if they did not adopt these combinations. This particular analysis shows that adoption of a combination of climate-smart practices leads to statistically significantly higher farm revenue, by NAD 1963. The implication is that combining adaptation strategies leads to a synergetic gain.

2 NAD is Namibian dollar, equivalent to 0.067 USD.

Table 4: Average conditional effects estimation of the effects of adopting climate-smart technologies on farm income

	Adopter sample households				
Outcome	Actual net farm income if the household did adopt	counterfactual farm income if the household did not adopt	Adoption effects		
				t-value	P-value>0
crop/livestock/water adaptation	4866.916 (198.5388)	2903.374 (192.4784)	2334.585(327.5473) ***	7.1275	0.0000
a combination of crop/livestock/water adaptation or all three	5333.737 (212.6008)	2999.153 (249.1749)	1963.542(276.5241) ***	7.1008	0.0000

As a robustness check, we computed the net gains in revenue from adoption by using the same categories of adaptation (crop, livestock, water-based) but adding one more adaptation strategy to the crop and water adaptation categories. Hence, in this particular analysis, we included use of soil and water conservation methods in addition to adoption of drought-tolerant crop varieties and sequential timing of cropping (e.g. planting different portions of land at different times in season). In the water adaptation category, we added conserving and protecting some water sources for the dry season, in addition to using earth dams. The purpose of expanding this categorization is to ensure robustness in our definition of the adaptation categories[3]. Table 5 presents the results from the analysis of these new sets of adaptation. The results corresponding to these adaptation combinations mimic the results presented in Table 4, with combinations yielding significant and positive returns, compared to the singular adaptation, which yields insignificant (statistically zero) returns.

[3] It should be noted that the results in Table 5 are the outcomes (post-estimation computations) of a multinomial switching regression estimation, corresponding to the adaptation categories discussed here. However, the estimation results corresponding to the regression are omitted for ease of discussion.

Table 5: Average conditional effects estimation of the effects of adopting climate-smart technologies on farm income (robustness test-1)

	Adopter sample households				
Outcome	Actual net farm income if the household did adopt	counterfactual farm income if the household did not adopt	Adoption effects		
				t-value	P-value>0
crop/livestock/water adaptation	5597.157 (244.6257)	3717.588 (212.8703)	1879.569 (324.2769)***	5.7962	0.0000
a combination of crop/livestock/water adaptation or all three	4866.916 (198.5388)	2903.374 (192.4784)	927.423 (328.7522)***	2.8210	0.0050

Another robustness check we employed is reducing the number of adaptation categories compared to those we considered in Table 4. We included adopted drought-tolerant crop varieties, while the rest remain the same as those in Table 4[4]. The results are presented in Table 6 and show that adopting singular adaptation technologies led to a farm income gain of NNAD 2814. However, the net farm income gain from adoption of combinations of adaptation practices is NNAD 2390 and is statistically significant. This suggests that, given the diverse nature of Namibian agriculture, gains from adaptation may not necessarily be complemented by the adoption of cross-sectoral practices.

Table 6: Average conditional effects estimation of the effects of adopting climate-smart technologies on farm income (robustness test-2)

	Adopter sample households				
Outcome	Actual net farm income if the household did adopt	counterfactual farm income if the household did not adopt	Adoption effects		
				t-value	P-value>0
crop/livestock/water adaptation	5236.559 (207.7831)	2421.965 (749.1483)	2814.594(777.4297)***	3.6204	0.0003
a combination of crop/livestock/water adaptation or all three	4894.317 (196.4675)	2565.304 (273.5655)	2329.014(336.8049)***	6.9150	0.0000

6. Conclusion

Namibia is one of the driest countries in the sub-Saharan Africa region. The viability of the agricultural production systems in Namibia, as in many semi-arid areas in Sub-Saharan Africa, is highly constrained by the threats of climate change. Policies to enhance agricultural productivity, therefore, cannot be seen as separate from efforts to ensure effective adoption practices against climate change vagaries. However, the adoption of climate-smart agriculture strategies and technologies has been slow in Namibia (Davies et al., 2019).

Our estimation strategy employs a multinomial endogenous switching regression model of adoption of climate-smart technologies and agricultural revenues, comprised of crop and livestock income. The method is chosen to account for the simultaneous availability of multiple climate-smart technologies, the heterogeneity in the decision to adopt or not a particular strategy, and for unobservable characteristics of farmers.

The results show that the adoption of climate-smart agriculture practices consistently increases agricultural income. Specifically, climate-smart practices which include crop, livestock and water-related adaptation technologies have the potential to increase crop income in the range of NAD 927-NAD 2814. In addition, we seek to determine whether the effect of adopting singular or a combination of adaptation practices yields better results in terms of farm income. We also found interesting results from differential impacts of singular versus combination adoption, with the former having higher impact on income as the number of diverse activities increases. The implication is that the diverse nature of Namibian agriculture can increase the gains from adaptation but may not necessarily be complemented by the adoption of cross-sectoral practices.

A major shortcoming of the study is the fact that the empirical analysis is based on cross-sectional data. Future availability of panel data would enable controlling for unobserved heterogeneity at the household level. This is particularly important when adaptation decisions are largely attributable to unobserved household characteristics such as propensity to adopt, farmer skills, access to technology, past experience with technology, etc. Another potential area of future research is extending the sample size to include households with no adaptation technology so that a proper counterfactual of non-adaptation is constructed.

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Table A1: Parameter estimates of test on the validity of selection instruments

	farm income
Age of the household head	28.189+
	(1.67)
gender of the household head	446.058
	(0.70)
training of the household head	280.108
	(1.46)
Marital status of the household head	-490.982**
	(-2.71)
Family size	28.274
	(0.31)
Number of plots	-311.402
	(-0.34)
Access to fertile plots	2024.990***
	(3.58)
Quantity of fertilizer used	2.781
	(0.91)
Quantity of seeds used	0.064
	(0.03)
Number of livestock owned (in Tropical Livestock Units)	79.709***
	(4.54)
cropping season	564.297
	(0.95)
previous experience of reduced yield	1253.746+
	(1.86)
info_climate	-1189.724+
	(-1.94)
familyout	8.930
	(0.21)
_cons	2243.865
	(1.27)
pseudo R-sq	
F	5.538
N	528
Wald test on instrumental variables (F-stat.)	1.89
Prob > F	0.1518

Table A2: Estimates of Farm Income Equations by Multinomial Endogenous Switching Regression Model (second stage estimation results)

	Singular adaptation	Combination adaptation	Other adaptation
Age of the household head	5.275	62.162	0.704
	(0.10)	(0.74)	(0.01)
gender of the household head	-743.956	2734.775+	-5089.359
	(-0.45)	(1.75)	(-1.33)
training of the household head	407.179	-25.159	592.660
	(0.60)	(-0.09)	(0.78)
Marital status of the household head	-66.862	-447.155	-2131.165*
	(-0.08)	(-1.11)	(-2.07)
Family size	-179.823	313.461	-5.248
	(-0.44)	(1.40)	(-0.03)
Number of plots	203.995	-1358.786	1738.525
	(0.05)	(-0.85)	(1.12)
Access to fertile plots	3028.174	2399.140	-1054.977
	(1.13)	(1.25)	(-0.68)
Quantity of fertilizer used	-3.564	0.755	14.907
	(-0.00)	(0.12)	(0.14)
Quantity of seeds used	-2.746	2.354	3.157
	(-0.31)	(0.02)	(0.03)
Number of livestock owned (in Tropical Livestock Units)	226.201**	209.442*	65.923*
	(3.05)	(2.29)	(2.15)
cropping season	-542.930	-2412.607**	4286.817**
	(-0.30)	(-2.82)	(2.71)
previous experience of reduced yield	-52.217	-1651.516	-1222.903
	(-0.02)	(-0.97)	(-0.88)
crop related climatic exposure	622.355	-477.756	1882.107
	(0.18)	(-0.15)	(1.39)
livestock related climatic exposure	2441.342	5265.954	3919.237
	(0.34)	(1.32)	(0.73)
water related climatic exposure	870.727	-4353.250*	-6812.277
	(0.19)	(-2.36)	(-1.11)
_cons	9814.817	2768.918	6174.509
	(1.03)	(0.48)	(0.76)
Anciliary			
Sigma2	50493300.305	87102398.837	4.787e+08+
	(0.28)	(1.05)	(1.90)
rho1	0.441	0.724***	0.230
	(1.36)	(3.67)	(0.79)
rho2	0.157	-0.598***	-0.399
	(0.45)	(-5.32)	(-1.24)
pseudo R-sq			
F			
N			
t statistics in parentheses			
="+ p<0.10	* p<0.05	* p<0.05	* p<0.05