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Weather at Different Growth Stages, Multiple Climate Smart Practices and Farm Level Risks

Panel Data Evidence from the Nile Basin at Ethiopia

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Weather at Different Growth Stages, Multiple Climate Smart Practices and Farm Level Risks: Panel Data Evidence from the Nile Basin of Ethiopia

Hailemariam Teklewold and Alemu Mekonnen*

Abstract

The present study investigates the effects of combinations of climate smart agricultural practices on risk exposure and cost of risk. We do this by examining the different risk components – mean, variance, skewness, and kurtosis – in a multinomial treatment effects framework by controlling weather variables for key stages of crop growth. We found that adoption of combinations of practices is widely viewed as a risk-reducing insurance strategy that can increase farmers' resilience to production risk. The hypothesis of equality of weather parameters across crop development stages is also rejected. The heterogeneous effects of weather across crop growth stages have important implications for climate change adaptation to maximize quasi-option value. For a country that has a vision to build a climate resilient economy, this knowledge is valuable to identify a combination of climate smart practices that minimizes the production risk under variable weather conditions.

Keywords: risk; weather; crop growth cycles; multiple practices; impact

JEL Codes: Q12, Q54

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1. Introduction

Smallholder agriculture in developing countries has always been a risky effort. Farmers commonly face severe yield variability and low agricultural productivity due to low adoption of farm technologies, unpredictable weather shocks and damages from pest and disease infestations. Empirical evidence indicates that risk aversion is a basic characteristic of smallholder farmers (Kim and Chavas 2003). In a developing country like Ethiopia where markets for insurance and credit are poorly functioning or largely absent, risk averse farmers exhibiting downside risk aversion have developed different traditional risk management strategies to increase farm productivity and manage production risk (Kim et al., 2012).

Various studies analyze the effect of agricultural practices on yield level and yield risk. Recent studies in the Nile Basin areas of Ethiopia (Teklewold et al., 2017) and in Malawi (Asfaw et al., 2016) reported significant increases in farm returns due to adoption of combinations of climate smart practices (CSAs)[1]. Mukasa (2018) investigated the empirical linkages between production risks and the adoption of modern inputs among smallholder farmers in Tanzania and Uganda. Kassie et al. (2015) analyzed the effect of sustainable intensification practices on production risk in Ethiopia and found the effect on skewness dominated the effect on variance, resulting in a decrease in risk premium[2]. Reynaud (2009) studied farmers' management of drought risk and found that crop diversification is important in mitigating production losses. However, there is a paucity of information on the cost of facing weather shocks and the synergies between various agricultural technologies and management options for managing exposure to adverse weather shocks.

The objectives of this study are to examine the role of a portfolio of potential climate smart practices – agricultural water management, improved crop varieties and fertilizer – in exposure to production risk and risk premium; and to analyze the effect of weather shocks at different stages of crop growth cycles on production risk in the Nile Basin of Ethiopia.

We borrow a portfolio theory from financial analysis to study farmer's risk management with a combination of CSAs. The study unraveled the risk premiums by specifying the cost of adverse weather shocks and explicitly capturing the different risk components – mean, variance, skewness, and kurtosis. This study addresses a concern raised in previous studies of production risk: by considering the skewness without kurtosis, the overall effect of a combination of

[1] CSA reflects agricultural practices informed by climate impacts on agriculture, including practices that strengthen farmers' resilience to climate change (FAO 2011; Arslan et al., 2013).

[2] By weighting both upside volatility and downside movements equally, the mean-variance approach does not distinguish the downside risk from the upside risk.

technologies and management options on production risk is likely overestimated because a change in skewness distribution (the tail mass) is often accompanied by a change in kurtosis (the peak) (Just and Pope, 1979; Ramirez et al., 2003). By contrast, jointly considering skewness and kurtosis allows a more accurate approximation of the unknown production function (distribution) and its underlying production risks, given that the number of potential distributions defined by the moments decreases as higher moments become available (Awondo et al., 2017). Hence, failure to consider the relevant moments may nullify the cost of risk and household's welfare analysis through erroneous approximation of expected utility maximization.

Our study adds value to existing literature on the economics of climate change adaptation in the following ways. First, the paper contributes to the limited literature on adoption of a portfolio of CSAs in the face of changing weather conditions and their effect on different risk components. In this study, we consider a combination of adaptation measures that build upon risk-reducing options through agricultural water management (AWM) and increase farm productivity through fertilizer application and improved crop varieties. AWM is important for managing the production risk arising from weather variation (Boggess et al., 1983). Adoption of modern seeds and fertilizers increases mean yields but also increase the variance of yields (Just and Pope, 1979; Paulson and Babcock, 2010).

Second, from a data utilization point of view, we explicitly account for weather shocks at different growth stage of the crops and investigate the correlation between production risk and weather disaggregated by growing stages. It is not sufficient to evaluate risk based on the calendar or season, which implicitly assumes that the weather effects at different growth stages remain fixed, and ignores the complex interactions of farmer behavior to adjust the timing and level of inputs with crop growth (Ortiz-Bobea, 2013). For instance, the effect of temperature on corn yields in the United States is nonlinear (Schlenker and Roberts, 2009). It is also unclear at which stage of crop growth the weather variables have the most influence on the farm economy. Some agronomic evidence has shown that stress during the flowering period reduces yield more than at any other stage of growth (Fageria et al., 2006). Closing this knowledge gap for smallholder agriculture in the developing world requires investigation of the temporal heterogeneity of weather shocks on different crop growth stages and the corresponding impacts on production risk. Therefore, as in Kawasakil et al., (2016) and Ricome et al., (2017), we follow a typical agronomic-based literature classification to distinguish the crop growing cycle into three key stages (i) juvenile and earlier vegetative phases, (ii) later vegetative phases and flowering and (iii) grain development (fructification).

The paper proceeds as follows. The next section presents the empirical approach with discussion on estimation of risk and cost of risk and the econometric framework to evaluate how technology and management options affect risk exposure. Section 3 provides a description of the study areas, data, and sampling. This is followed by presentation of our estimation results. The final section concludes.

2. Empirical Strategy

The empirical estimation approach involves the computation of production risk and risk premiums, using econometric methods to evaluate how technology and management options affect the different risk components.

2.1 Measuring Exposure to Risk: A Moment Approach

Our analysis of production risk relies on a moment-based approach that evaluates the mean, variance, skewness and kurtosis of farm returns conditional on weather, location, farm and managerial characteristics (Antle 1983; Kim and Chavas 2003). Antle's (1983) framework of a production risk analysis divides the variation in farm return into the mean effect of the explanatory variables on farm return and the unexplained variation of farm return (the error distribution):

$$y = g(w,v) = f_1(w,\gamma_1) + e \tag{1}$$

where y is the farm net return per hectare, v is a vector of random variables reflecting production risk (e.g., pests and diseases, rainfall variability, and drought), $f_1(w,\gamma_1) \equiv E[y]$ is the mean return production function (the first central moment), and $e \equiv g(w,v) - f_1(w,\gamma_1)$. γ is an unknown parameter to be estimated. e is a random variable that captures the uncertainty faced by farmers and satisfies $E(e) = 0$. w is the vector of inputs (e.g., seeds, manure, pesticides, labor), assets (e.g., land, equipment, livestock), and plot characteristics (e.g., fertility, slope, depth, distance, plot investment) impacting the distribution of farm returns under uncertainty.

The kth central moments of farm returns about its mean are defined as:

$$E\left\{\left[g(w,v) - f_1(w,\gamma_1)\right]^k \middle| w\right\} = e^k \quad \text{for k = 2, 3, 4} \tag{2}$$

This can generate consistent estimates of the moments of e, conditional on w such that $f_2(w,\gamma_2)$ or e^2 is the second central moment (variance), $f_3(w,\gamma_3)$ or e^3 is the third central moment (skewness) and $f_4(w,\gamma_4)$ or e^4 is the fourth central moment (kurtosis) of the farm return function. The second central moment captures the variability of farm returns around its mean. The skewness measures asymmetry of the return distribution, with a negative skewness capturing exposure to losses located in the lower tail of the distribution (downside risk). The problem with variance is that it takes both upside and downside variability of the distribution. Kurtosis risk is commonly referred to as "fat tail" risk: the situation of having more observations at either extreme than the thin tails of the normal distribution. A high kurtosis value means more of the variance is the result of infrequent extreme deviations. Farmers who are usually risk averse prefer positive skewed distributions to negatively skewed ones, as well as distributions of returns with a lower possibility for significant changes (lower kurtosis) to those with a higher possibility of jumps (higher kurtosis).

2.2 Measuring the Cost of Risk

In this section, we present the measure of the cost of risk, following Antle (1983); Kim and Chavas et al. (2003); Kassie et al. (2015) and Awondo et al., (2017). The cost of risk may be derived by a sure amount R satisfying:

$$EU(y) = U[E(y) - R] \tag{3}$$

where $[E(y) - R]$ is the certainty equivalent of farm returns, as in Pratt (1964). R is the cost of risk measured by risk premium following Arrow-Pratt and defined as the largest amount of money that the farmer is willing to pay to replace the random variable y by its expected value E(y). Risk aversion implies that R > 0.

In order to estimate and evaluate the cost of risk, we represent the risk preference by the constant relative risk aversion (CRRA) utility function $U(y) = \left(y^{(1-b)}\right)/\left(1-b\right)$, where $y > 0$ is farm return and $b > 0$ is the Arrow-Pratt relative risk aversion coefficient (Kim and Chavas, 2003; Kassie et al., 2015; Mukasa 2018).

Kim and Chavas (2003) indicated that the risk premium capturing the first four moments of farm return distribution can be computed as follows:

$$R = \left[-\frac{1}{2}\omega_2 E[y-E(y)]^2 - \frac{1}{6}\omega_3 E[y-E(y)]^3 - \frac{1}{24}\omega_4 E[y-E(y)]^4 \right] \tag{4}$$

where $\omega_2 = -\frac{U''(\cdot)}{U'(\cdot)}$; $\omega_3 = -\frac{U'''(\cdot)}{U'(\cdot)}$; $\omega_4 = -\frac{U''''(\cdot)}{U'(\cdot)}$ and $E[y-E(y)]^i$ are the i^th moments of the distribution of farm returns: ω_2, ω_3 and ω_4, all evaluated at *E*(y).

Then, the cost of risk in (4) becomes:

$$R = \frac{b}{2}\frac{E[y-E(y)]^2}{E[y]} - \frac{b(b+1)}{6}\frac{E[y-E(y)]^3}{E[y]^2} + \frac{b(b+1)(b+2)}{24}\frac{E[y-E(y)]^4}{E[y]^3} \tag{5}$$

The above equation explains a decomposition of the cost of risk under CRRA risk preferences with a risk aversion parameter of 3, defined as moderately risk averse farmers (Binswanger 1980; Yesuf and Bluffstone 2009). It provides an explicit tool for the empirical assessment of the cost of risk measured through the partial mean, partial variance, partial skewness, and partial kurtosis. Using this equation and the econometric results, we decompose the costs of risk into three parts (the effect of variance, skewness and kurtosis) by each alternative combination of CSA practices. Jointly considering both skewness and kurtosis could result in situations where they reinforce or cancel each other depending on the shape of the farm return distribution and how it responds to changes in adoptions of various combinations of CSA (Awondo et al., 2017). In a symmetric distribution, the effects in both ends of the tails could cancel out, resulting in little effect on downside risk. However, this may not be the case in a skewed-kurtotic distribution, which requires the joint effect on both skewness and kurtosis to be considered to fully evaluate the effect on downside risk. This is because, under such a distribution, the effects at the tails might not cancel out, in that an increase in skewness may or may not be associated with a decrease in downside risk exposure.

2.3 Impacts of Adoption: Treatment Effects with Endogenous Treatment

We begin by presenting a general representation of our model which has two modules: a choice of combinations of CSA and a production risk module. The two elements are linked because combinations of CSA choices are regressors in the production risk estimation and because there are common unobservable (latent) factors. Hence, we employ a treatment-effects model to analyze the effects of an endogenous multinomial treatment on a non-negative integer valued outcome, as in Deb and Trivedi (2006). We develop a treatment-outcome model for the multinomial choice of a combination of CSA and farmers' production risk with a view to evaluating the treatment effect of endogenous choice of CSA on production risk outcomes. We specify a joint distribution of endogenous treatment and outcome using a latent factor structure. Latent factors are incorporated into the treatment and outcome equations to allow for idiosyncratic influences on technology choice to affect risk, thus enabling us to make a distinction between selection on unobservables and observables (Heckman 1978). These idiosyncratic influences are interpreted as unobserved heterogeneity. The model captures heterogeneity in the production risk response to the choice of various combinations of CSA, which is known to be an important feature of program impact evaluation studies (Heckman 1978).

Let d_j be binary variables representing the observed choice of the combination of practices (with j = 1, . . ., 8 as shown in Table 1). We treat non-adoption of any of the practices as the baseline choice. The choice of practices is modeled through a density function g that characterizes the multinomial choice:

$$\Pr(d_j \left| X_{ij}, I_i \right.) = g(\beta_1 X_{ij} + \alpha_1 l_{ij}, \beta_2 X_{ij} + \alpha_2 l_{ij}, ..., \beta_j X_{ij} + \alpha_j l_{ij}) \tag{6}$$

Table 1. Frequency (%) Distribution of CSA Packages used on Crop Plots in Ethiopia

Choice (j)	CSAs package[Ψ]	Improved variety (V_a)		Fertilizer (F_e)		Agricultural water management (A_w)		Frequency (%)		
		Va_1	Va_0	Fe_1	Fe_0	Aw_1	Aw_0	2015	2016	Average
1	$Va_0F_{e0}A_{w0}$		√		√		√	29.69	18.07	24.29***
2	$Va_1F_{e0}A_{w0}$	√			√		√	2.77	2.10	2.46**
3	$Va_0F_{e1}A_{w0}$		√	√			√	18.26	13.44	16.02***
4	$Va_0F_{e0}A_{w1}$		√		√	√		13.53	24.27	18.53***
5	$Va_1F_{e1}A_{w0}$	√		√			√	10.63	7.45	9.15***
6	$Va_1F_{e0}A_{w1}$	√			√	√		1.68	1.91	1.79
7	$Va_0F_{e1}A_{w1}$		√	√		√		15.74	20.75	18.07***
8	$Va_1F_{e1}A_{w1}$	√		√		√		7.70	12.01	9.70***

[Ψ]Each element in a CSA combination (package) consists of a binary variable for a CSA /Improved crop variety (V_a), inorganic fertilizer (F_e), agricultural water management (A_w)/, where the subscript refers to 1= if adopted and 0 = otherwise.

*, ** and *** indicate that the difference between the two years is statistically significant at 10%, 5% and 1% level, respectively.

Let e_{it}^{k*} denote the value of the latent variable underlying the observed values of production risks for individual *i* at time *t* (variance, skewness and kurtosis), e_{it}^{k}. The outcome or production risk equation for individual i, $i=1,...,N$ is formulated as:

$$E(e_i^k \mid d_i, X_i, l_i) = \beta X_i + \sum_{j=1}^{j} \gamma_j d_{ij} + \sum_{j=1}^{j} \lambda_j l_{ij} \tag{7}$$

where X_i is a set of exogenous covariates with associated parameter vectors β; and γ denotes the treatment effects relative to the baseline. The term l_{ij} represents the unobserved characteristics common to individual i's choice of the combination of practice j and the production risk outcome of that individual. The α, factor loadings, are parameters associated with the latent factors in the choice of practices and cause adoption status to be endogenous with respect to production risks. Because the latent factors l_{ij} enter both the choice and the outcome equations, they capture the unobservable individual-specific factors that induce self-selection into choice of practices. The joint model allows direct interpretation of selection effects by way of the factor loadings (λ_j). If λ_j <0, unobserved individual-specific factors that induce a household to adopt combinations of practices are associated with a lower level of production risks. When λ_j >0, adverse selection is present; i.e., the treatment and outcome are positively correlated through unobserved characteristics.

In estimating equation (7), some issues concerning model identification arise due to the introduction of endogenous CSA practices. In principle, the identification of the causal parameters through nonlinear functional forms is feasible, but for more robust identification the traditional approach is through nontrivial exclusion restriction or instrumental variables. Therefore, one needs variables in the data set that are correlated with the choice of CSA but are, conditional on exogenous variables in the outcome equation, uncorrelated with the production risk variables. Following Asfaw et al., (2016), we use long term (1983-2015) historical climate variables that capture rainfall and temperature patterns as identifying instruments. As farmers form expectations about the climatic conditions of their area based on their experiences, the instruments are assumed to affect the household's decision on the choice of CSA during the current year, but they are assumed to not affect production risk except indirectly through the choice of CSA. Consequently, results should be treated as identifying the causal effects of the particular CSA practice or combination.

3. Data and Sampling

3.1 Study Areas and Sampling

Data used in this study are from a panel of farm household survey data collected in the 2015 and 2016 cropping seasons covering five regional states of the Ethiopian part of the Blue Nile Basin: Amhara, Oromia, Tigray, Benshangul-Gumuz and SNNP. The basin covers about two-thirds of the country's land mass and contributes nearly 40% of its agricultural products and 45% of its surface water (Erkossa et al., 2014). The areas selected represent different agro-ecological settings and are characterized by highly rugged topography, with altitudes ranging from 800 to over 3000 meters above sea level. The farming system of the basin can be broadly categorized as a mixed crop-livestock farming system, where over 90% of the cultivated area is covered by the cereal based farming system (Erkossa et al., 2014). Although both annual and perennial crops are grown in the area, the annual crops cover more than 98% of the plots. We thus limit our analysis to the annual crop plots. The main crops grown in the study areas are maize, wheat, teff, barley and legume.

The sampling frame considered the traditional typology of agro-ecological zones in the country (i.e., *Dega* (cool, humid, highlands), *Weina-Dega* (temperate, cool sub-humid, highlands), *Kolla* (warm, semi-arid lowlands), and *Bereha* (hot and hyper-arid)). The sample was chosen through a multistage proportionate random sampling process. The procedure was employed to select villages from each district, and households from each village. The sampling frame selected the *woredas*[3]in such a way that each class in the sample matched the proportions for each class in the entire Nile Basin. First, twenty woredas from the five regional states were selected (i.e., 3 each from Tigray and Benshangul-Gumuz, 6 from Amhara, 7 from Oromia, one from SNNP). This resulted in a random selection of fifty farmers from each woreda. After cleaning inconsistent responses, our sample is composed of a total of 4365 farming plots with 929 farm households in 2015, while the follow-up survey in 2016 covers 921 households[4]. In both years, a structured questionnaire was prepared, and the sampled respondents were interviewed using trained and experienced enumerators knowledgeable of the local language.

3.2 Data Description

As part of the household survey, we collected data on household characteristics, including asset endowments, quantity of livestock, crops produced, agricultural practices used, and methods and frequency of land preparation and other farming operations. The structured plot-level questionnaire aimed to gather information on soil characteristics including slope, fertility and depth of the soil, details on crop management (sowing dates, crop choice, harvesting time) and different types of plot-level shocks affecting crop production. The survey also recorded geo-referenced household-level latitude and longitude coordinates using hand-held Global Positioning System (GPS) devices, which allow for the linking of household-level data to historical temperature and precipitation data.

Table 1 presents the proportions of farming plots cultivated under the different combinations of practices. The climate smart practices considered in this study include agricultural water management, improved crop seeds, and inorganic fertilizer, providing eight mutually exclusive combinations of practices (2^3). On average, about 24% of the plots did not receive any of the practices ($Va_0Fe_0Aw_0$), while all three practices were simultaneously adopted on only 10% of the plots ($Va_1Fe_1Aw_1$). The share of plots without any of the practices decreased from 30% in 2015 to 18% in 2016, but the share of plots with all three practices increased from 8% to 12% in the same period of time. Table 2 shows the unconditional adoption probabilities of the choice variables and the average level for the outcome variable. The output variable is net farm income (Birr/hectare), which is the crop income after fertilizer, seed, labor and pesticides costs have been accounted for[5].

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[3]An administrative division equivalent to a district.
[4]The attrition (less than 1%) is relatively small given sample size. This is true attrition; the respondent either left the village or passed away.
[5] Birr is the Ethiopian currency, with a conversion rate of 1Birr ≈0.04 USD at the time of this study (May 2017).

Table 2. Definition and Summary Statistics of Choice and Impact Variables

Variables	Definition	Year		
		2015	2016	Average
Choice variables				
Improved variety	Improved crop variety adopted (1=if yes; 0 = no)	0.227	0.235	0.231***
Inorganic fertilizer	Inorganic fertilizer adopted (1=if yes; 0 = no)	0.523	0.536	0.529***
Agricultural water management	Agricultural water management practices adopted (1=if yes; 0 = no)	0.387	0.589	0.481***
Impact variables				
Crop income	Net crop production value (Birr/ha)	12474.93	11854.37	12186.28
		(135.31)	(163.46)	(105.01)**
e1	First moments	-2266.86	241.24	-1100.21
		(11982.64)	(12084.82)	(12094.51)
e2	Second moments ($X10^5$)	1486.93	1460.67	1474.72
		(1714.08)	(2172.57)	(1940.81)
e3	Third moments ($X10^7$)	-4168.73	6247.39	6763.39
		(6356.60)	(9206.38)	(7829.39)
e4	Fourth moments ($X10^{13}$)	5148.45	6852.56	5941.12
		(2576.07)	(4081.17)	(3362.95)

*, ** and *** indicate that the difference between the two years is statistically significant at 10%, 5% and 1% level, respectively. Numbers in parentheses are standard deviation.

Table 3 presents the control variables used in the empirical analysis, their description, and summary statistics for the full sample and the eight sub-groups (by the combination of practices). The control variables include natural capital (soil depth, slope, fertility), social capital and networks (membership in community-based institutions, kinship network), shocks (self-reported rainfall shocks and plot-level crop production disturbances), physical capital (farm size/ livestock), access to services and constraints (distance to main market, access to credit, extension service and climate information), human capital (family size, household head education, gender and age), plot distance to dwelling, geographic location and climate variables (temperature, intensity and variability of rainfall). The detailed descriptions of these variables are available in Teklewold et al. (2017). Below, we focus on describing these variables in relation to climate change adaptation literature.

Table 3. Variables Definition and Descriptive Statistics by Combination of Climate Smart Practices

Variable	Description	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_1Fe_0Aw_1$	$Va_0Fe_1Aw_1$	$Va_1Fe_1Aw_1$	All Mean	All Std.dev
Household features											
Gender	Sex of the head (1=if male)	0.89	0.90	0.86	0.91	0.93	0.87	0.89	0.90	0.89	-
Age	Age of the head, years	51.64	50.09	53.08	51.97	52.03	50.38	52.79	51.37	52.09	12.59
Education	Household education, years	0.33	0.42	0.29	0.35	0.39	0.38	0.33	0.40	0.34	0.48
Famlysize	Family size	8.16	8.36	8.34	8.15	8.59	8.11	8.18	8.37	8.25	2.36
Resource constraints											
Farmsize	Farm size, ha	3.98	4.77	3.82	3.60	4.00	3.93	4.02	3.78	3.89	3.15
Tlu	Livestock size	4.51	4.94	4.61	4.60	5.04	4.42	4.65	4.86	4.66	3.34
Credit	Credit constraint (1=if yes)	0.52	0.57	0.44	0.48	0.46	0.57	0.44	0.44	0.47	-
Asset	Value of household and farm assets, ‘000 Birr	23.55	21.97	32.05	22.12	33.90	38.67	29.16	43.45	28.77	59.89
Extension, information and market											
Teleph	Own telephone (1=if yes)	0.39	0.44	0.49	0.38	0.51	0.52	0.54	0.56	0.46	-
Distoutmkt	Walking distance to output markets, minutes	64.08	59.81	65.73	66.66	56.84	61.30	65.14	56.45	63.46	46.37
Distinputmkt	Walking distance to input market, minutes	53.29	54.44	58.34	52.14	48.58	52.11	56.71	46.40	53.41	38.44
Totextcontact	Number of topics introduced by the extension agents	6.74	7.55	7.59	7.58	7.62	7.62	7.42	8.02	7.39	3.42
Extconfdnt	1=if the household is confident about skill of extension agent	0.76	0.75	0.71	0.73	0.75	0.77	0.67	0.71	0.72	-
Infoclimate	1=if farmer is informed about climate change	0.73	0.72	0.85	0.77	0.85	0.74	0.80	0.85	0.79	-
Social capital network											
Relative	Number of relatives in and outside the village	17.94	20.13	22.16	14.94	20.94	16.63	19.46	23.53	19.18	28.07
Totgroup	Number of groups where a farmer is a member	3.93	4.19	4.07	4.44	4.50	4.62	4.62	5.27	4.37	2.35
Agrimemb	1=if member of agricultural producer	0.49	0.56	0.46	0.52	0.56	0.61	0.52	0.67	0.53	-
Finmemb	1= if member of a credit and saving groups	0.80	0.76	0.86	0.88	0.89	0.78	0.90	0.90	0.86	-
Socmemb	1=if member of social related groups	0.89	0.90	0.96	0.95	0.97	0.93	0.97	0.97	0.94	-
Shocks											

Variable	Description	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_1Fe_0Aw_1$	$Va_0Fe_1Aw_1$	$Va_1Fe_1Aw_1$	All Mean	All Std.dev
Rainindex	Rainfall disturbance index (1=best)	0.70	0.70	0.66	0.67	0.71	0.63	0.66	0.66	0.68	0.30
Plotindex	Plot level disturbance index (1=worst)	0.16	0.13	0.18	0.14	0.14	0.13	0.18	0.17	0.16	0.17
Relygovt	1=if rely on government assistance in case of crop failure	0.44	0.48	0.55	0.49	0.50	0.46	0.52	0.53	0.50	-
Farm features											
Plotdist	Walking distance of the plot from home, minutes	15.65	12.80	14.65	14.64	13.81	14.83	15.36	15.17	14.95	20.03
Tenure	1=if own the plot	0.87	0.89	0.80	0.89	0.84	0.92	0.84	0.86	0.85	-
Highfert	1=if highly fertile soil plot	0.35	0.29	0.36	0.36	0.37	0.46	0.38	0.42	0.37	-
Midfert	1=if medium fertile soil plot	0.52	0.60	0.48	0.52	0.50	0.49	0.50	0.48	0.51	-
Flatslop	1=if flat slope plot	0.60	0.57	0.71	0.62	0.62	0.67	0.65	0.63	0.64	-
Midslop	1=if medium slope plot	0.36	0.38	0.25	0.33	0.33	0.32	0.32	0.32	0.32	-
Depdepth	1=if deep depth soil plot	0.45	0.43	0.48	0.46	0.47	0.52	0.49	0.49	0.47	-
Middepth	1=if medium depth soil plot	0.42	0.48	0.39	0.45	0.41	0.41	0.41	0.39	0.42	-
Manure	1=if manure was applied in the plot	0.27	0.41	0.26	0.30	0.33	0.46	0.29	0.41	0.30	-
Cereal	1=if the plot is with cereal crops	0.58	0.79	0.85	0.59	0.93	0.66	0.83	0.89	0.74	-
Legume	1=if the plot is with legume crops	0.28	0.11	0.07	0.25	0.04	0.17	0.06	0.04	0.15	-
Climate											
Rain_Long	Long term mean monthly rainfall in the main season in mm (1983-2014)	148.29	164.04	126.89	154.73	149.07	163.64	136.70	144.53	144.33	41.63
Temp_Long	Long term average daily temperature in ^{0}C (1983-2014)	18.09	18.46	17.97	17.84	17.55	18.35	18.05	17.98	17.97	2.01
Number of observations (plots)		2265	229	1494	1728	853	167	1685	905	9326	

Using the geo-referenced points recorded through GPS devices, we merged the household survey data with the climatic data to develop a set of variables to show the short- and long-term variation of precipitation and temperature shocks that were expected to affect the choice of combination of agricultural practices and production risks. We derived long-term mean rainfall and temperature and coefficient of variation in rainfall variables and included them in the technology choice model. The combined rain gauge and satellite-based monthly climate data (1983-2011) was obtained from the Ethiopian National Meteorology Agency (NMA). In Ethiopia, available weather stations are unevenly distributed and suffer from gaps in the time series. These impose severe limitations on the availability of climate information and services for different applications. Cleaning climate observations and combining station measurements with the complete spatial coverage of satellite estimates could help to fill these gaps and improve data availability over locations with few or no meteorological observations (Dinku et al., 2011). A collaborative effort has been made by the International Research Institute for Climate and Society at Columbia University with the NMA of Ethiopia and the University of Reading, UK, through combining station measurements with the complete spatial coverage of satellite estimates (Dinku et al., 2011). 30-year time series of rainfall and temperature data have been produced at 10 daily timescales for every 10-km grid over the country. The daily weather data from 2011-2015 were also obtained from different sources to complement the above data sets in terms of the remaining years. Temperature data were obtained from the Climate Research Unit (Harris et al., 2014), while the rainfall data were obtained from the Africa Rainfall Climatology dataset, version 2 (ARC-2) (Novella and Thiaw, 2013). This dataset consists of daily, gridded 0.1° X 0.1° estimates with a spatial domain of 40°S to 40°N in latitude, and 20°W to 55°E in longitude, encompassing the African continent.

To explore the assumption of weather additivity and heterogeneous impacts on production risk, the models requires matching data on weather conditions with crop progress at various times over the growing season. The daily availability of weather data during the production season in our data sets allowed us to match the rainfall and temperature data with the three growing stages of the production cycle and allows estimation of possible varying effects from intra-seasonal weather conditions on production risk. Crop stages reported by agronomists are not equally spaced in the growing season. They arguably correspond to visible markers that can be easily verified to simplify data collection. Some past studies (e.g., Kaufmann and Snell, 1997) have relied on weather variables matched to precise crop stages. In order to convey a more accessible crop stage, we divide the growing season into three segments. Daily weather data are then compiled by three growth stages that are defined based on a prefecture’s median planting, heading, and harvesting dates (i.e., because we don’t know the beginning of the second and third stages, we divide the production cycle into three, assuming that the largest share of the planted area reaches a particular stage).

Figure 1 illustrates kernel density plots for the weather variables created, including rainfall and temperature, as well as coefficients of variation in rainfall during the growing season, but for the different growth stages of the crops. As can be seen, there are differences in the distributions of rainfall and temperature as well as rainfall variability across the three growing stages. Table 4 clearly shows that the average amount of daily rainfall declines but the coefficient of rainfall variability increases as the crop development progresses. The results are in accord with agronomic science, in that the moisture and temperature requirements vary by the stage of crop development.

Table 4. Rainfall and Temperature Heterogeneity by Crop Development Stages

Crop growing stage	Description of the growing stage	Average daily rainfall (mm)	Coefficient of variation of daily rainfall	Average daily temperature (°C)
Stage 1	Germination	5.20 (2.67)	17.77 (9.06)	23.85 (3.66)
Stage 2	Heading	4.78 (2.32)	18.01 (8.48)	23.40 (2.57)
Stage 3	Maturity	2.11 (2.74)	31.73 (17.34)	23.63 (3.23)

Cognizant of the fact that meteorological stations are sparse and hence reliable rainfall data at micro-level is scarce in developing countries (Dinku et al., 2011), we also considered self-reported rainfall shocks. We followed Quisumbing (2003) to construct a subjective rainfall index based on respondents' satisfaction in terms of timeliness, amount, and distribution of rainfall. The individual rainfall index was constructed to measure the farm-specific experience related to rainfall in the preceding season, based on such questions as whether rainfall came on time at the start of the growing season, whether there was enough rain at the beginning of and during the growing season, whether the rain stopped on time and whether there was rain at harvest time. Responses to each of these questions (either yes or no) were coded as favorable or unfavorable rainfall outcomes. By averaging over the number of questions asked (five questions), we created an index that provides a value close to one for the best outcome and zero for the worst outcome.

We also created a farm-level shocks index capturing the most common shocks affecting crop production: pest and disease pressure; drought; flood; hailstorm; and erratic rainfall. Based on agronomy and climate literature, these shocks are hypothesized to affect the choice of practices and production risk. Farmers' responses to the presence of each of these shocks (either yes or no) were coded as unfavorable or favorable disturbance outcomes. By averaging over the number of shocks about which we asked (five questions), we created an index that provides a value close to one for the highest level of shocks.

To account for the effect of farm features on choice of practices and production risk, we control several plot-specific attributes, including soil fertility[6,] soil depth[7], plot slope[8], spatial distance of the plot from farmer's home (in minutes walking) and choice of crops grown. On average, 75% of land owners operate on about four parcels, each about 0.25 ha, and these plots are often not spatially adjacent (as far as 15 minutes walking time from the farmer's residence). The variable distance to plot is an important determinant of adaptation practices through its effect on increasing transaction costs on the farthest plot, particularly costs for transporting bulky materials/inputs associated with adaptation practices.

4. Empirical Results

Because we are primarily interested in the effect of adoption of combination of practices on production risk, we do not discuss the econometric estimates of CSA choice and estimates of the base (mean) model. The estimation results of the adoption of a combination of CSA practices are provided as supplementary materials in Table A1, and discussion of the empirical results is also available in Teklewold et al., (2017).

[6]The farmer's perception of each plot's soil fertility is ranked as "poor", "medium" or "good."
[7]The farmer's perception of each plot's soil depth is ranked as "deep", "medium deep" or "shallow."
[8]The farmer's perception of each plot's slope is ranked as "flat", "medium slope" or steep slope."

Table A1. Parameter Estimates for the Multinomial Treatment-Effects Regression of Various Combinations of Climate Smart Practices in Ethiopia

	$Va_1Fe_0Aw_0$		$Va_0Fe_1Aw_0$		$Va_0Fe_0Aw_1$		$Va_1Fe_1Aw_0$		$Va_1Fe_0Aw_1$		$Va_0Fe_1Aw_1$		$Va_1Fe_1Aw_1$	
Variables	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Household features														
Gender	-0.499*	0.293	-0.652***	0.157	0.030	0.163	0.102	0.212	-0.253	0.339	-0.375**	0.159	-0.228	0.193
ln (Age)	0.145	0.409	0.304	0.229	0.455**	0.202	0.177	0.258	0.452	0.470	0.587***	0.214	-0.398	0.259
ln (Education)	0.137	0.114	-0.109	0.068	0.105*	0.059	0.187***	0.071	-0.022	0.136	0.022	0.063	-0.056	0.074
ln (HHsize)	0.048	0.314	0.202	0.174	-0.066	0.160	0.172	0.197	-0.119	0.366	-0.333**	0.165	-0.070	0.198
Resource constraints														
ln (Farmsize)	0.481***	0.171	0.195**	0.098	-0.293***	0.087	0.012	0.113	0.171	0.209	0.219**	0.094	0.107	0.114
ln (Tlu)	-0.030	0.127	0.092	0.083	0.098	0.070	0.092	0.098	0.073	0.157	0.159*	0.083	0.114	0.094
Credit	0.118	0.291	-0.145	0.160	-0.086	0.148	0.008	0.182	0.628*	0.341	0.152	0.154	-0.027	0.180
ln (Asset)	0.089	0.117	0.053	0.066	-0.121**	0.057	0.145**	0.072	-0.170	0.129	-0.044	0.060	0.139*	0.072
Extension, information and market														
Teleph	0.720**	0.351	-0.292	0.197	0.000	0.176	0.105	0.223	0.565	0.437	0.054	0.185	0.064	0.221
ln (Disoutmkt)	0.320	0.211	-0.132	0.121	0.428***	0.107	-0.135	0.134	0.177	0.262	-0.218*	0.113	-0.093	0.134
ln (Disinputmkt)	0.083	0.196	0.498***	0.110	-0.039	0.090	0.044	0.123	-0.056	0.220	0.480***	0.102	0.134	0.121
Totextcont	0.129***	0.042	0.040*	0.023	0.110***	0.020	0.074***	0.027	0.069	0.052	0.042*	0.022	0.080***	0.027
Extconfdnt2	-0.326	0.201	-0.232**	0.111	-0.359***	0.103	-0.159	0.129	-0.314	0.239	-0.251**	0.107	-0.360***	0.127
Infoclimate	-0.179	0.298	0.021	0.181	-0.056	0.156	0.340	0.207	-0.349	0.391	-0.371**	0.173	0.139	0.207
Social capital network														
Relative	0.005	0.003	-0.004**	0.002	-0.001	0.002	-0.001	0.002	0.000	0.004	-0.003	0.002	0.003*	0.002
Totgroup	0.053	0.051	-0.109***	0.031	0.026	0.027	-0.016	0.033	0.146**	0.058	0.012	0.029	0.066**	0.031
Agrimemb	0.419*	0.216	0.316***	0.119	0.071	0.107	0.365***	0.134	0.340	0.253	0.139	0.114	0.724***	0.134
Finmemb	-0.213	0.268	0.064	0.159	-0.000	0.159	0.080	0.193	-0.278	0.324	-0.024	0.163	0.140	0.203
Socmemb	0.896**	0.387	0.456*	0.236	0.290	0.224	0.736**	0.310	0.245	0.492	0.460*	0.260	0.159	0.318
Shocks														
Rainindex	-0.708*	0.386	-0.318	0.221	-0.459**	0.203	-0.097	0.251	-1.308***	0.420	-0.021	0.217	-0.520**	0.249
Plotindex	-0.254	0.746	-0.836**	0.404	-1.108***	0.372	-1.207***	0.467	-1.652*	0.860	-0.237	0.388	-0.563	0.455
Relygovt	0.267	0.304	0.132	0.166	-0.394***	0.150	-0.050	0.190	-0.048	0.354	-0.206	0.157	-0.164	0.187
Farm features														
ln (Plotdist)	-0.116*	0.070	0.044	0.039	0.195***	0.037	0.065	0.045	0.136*	0.082	0.230***	0.038	0.252***	0.046
Tenure	-0.020	0.302	-0.449***	0.137	0.470***	0.143	-0.232	0.158	0.464	0.379	0.125	0.137	0.186	0.164
Higfert	-0.207	0.334	-0.419**	0.165	0.015	0.160	-0.010	0.195	0.777*	0.452	0.181	0.165	0.356*	0.202
Medfert	0.031	0.306	-0.208	0.149	-0.150	0.147	-0.020	0.180	0.330	0.437	0.233	0.152	0.337*	0.186
Flatslp	-0.659	0.430	-0.526**	0.246	-0.245	0.226	-0.307	0.288	0.628	0.780	-0.181	0.257	-0.656**	0.280
Medslp	-0.659	0.432	-0.573**	0.248	-0.217	0.227	-0.439	0.289	0.591	0.784	0.176	0.258	-0.497*	0.281

Variables	$Va_1Fe_0Aw_0$ Coefficient	SE	$Va_0Fe_1Aw_0$ Coefficient	SE	$Va_0Fe_0Aw_1$ Coefficient	SE	$Va_1Fe_1Aw_0$ Coefficient	SE	$Va_1Fe_0Aw_1$ Coefficient	SE	$Va_0Fe_1Aw_1$ Coefficient	SE	$Va_1Fe_1Aw_1$ Coefficient	SE
Depdpth	0.770**	0.357	0.327*	0.169	0.725***	0.167	0.527***	0.197	0.396	0.413	0.478***	0.170	0.421**	0.197
Meddpth	0.801**	0.342	0.269*	0.163	0.639***	0.161	0.483**	0.191	0.280	0.409	0.447***	0.164	0.378**	0.189
Manure	0.540***	0.208	-0.107	0.118	0.140	0.109	0.574***	0.132	0.801***	0.240	0.167	0.112	0.959***	0.131
Cereal	1.048***	0.283	0.816***	0.162	-0.240*	0.132	2.278***	0.265	0.538*	0.301	0.361**	0.145	1.446***	0.203
Legume	-0.533	0.388	-0.944***	0.212	-0.113	0.153	-0.184	0.332	0.141	0.363	-1.431***	0.199	-1.069***	0.297
Climate														
Rain_Long	0.058	0.047	0.121***	0.019	-0.021	0.021	0.115***	0.028	-0.074	0.052	0.122***	0.019	0.033	0.024
$(\text{Rain\_Long})^2$	-0.000	0.000	-0.000***	0.000	0.000	0.000	-0.000***	0.000	0.000**	0.000	-0.000***	0.000	-0.000	0.000
Temp_Long	-1.381*	0.711	3.294***	0.547	4.292***	0.511	0.652	0.578	2.772**	1.201	6.328***	0.635	1.257*	0.654
$(\text{Temp\_Long})^2$	0.033*	0.020	-0.090***	0.015	-0.123***	0.014	-0.023	0.016	-0.082**	0.034	-0.175***	0.018	-0.036*	0.018
Year (2016)	-0.300	0.208	0.035	0.117	1.362***	0.104	-0.123	0.131	0.314	0.236	0.885***	0.111	0.913***	0.128
Constant	-0.219	7.977	-45.696***	5.288	-42.562***	4.965	-22.345***	5.838	-31.966***	11.703	-75.106***	6.094	-21.950***	6.426
Joint significance of selection instruments χ^2 (5)	37.95***		112.17***		87.24***		123.76***		43.32***		173.96***		100.35***	
Joint significance of time varying covariates χ^2 (10)	19.82**		33.40***		20.70**		16.70*		13.58		34.30***		22.71***	
Joint significance of location variables χ^2 (4)	18.61***		147.05***		179.56***		129.66**		30.22***		165.84***		161.21***	

Number of observations = 9326; Wald $\chi^2(425)$ =5449 ; p >χ^2 = 0.000

As a precondition for the analysis of higher moments of estimation of the mean, variance, skewness and kurtosis functions, we first check that the distribution of e in eq. (1) is non-symmetric. To begin, we first perform a Jarque-Bera[9] (JB) analysis to test the null hypothesis that the farm returns distribution is symmetric. The sample value of the third moment is often compared with the population value for the normal distribution, 0, to characterize departure from normality. The result indicated that the third central moment of e for the entire distribution is positive (0.32) and statistically different from zero. We also find negative and statistically significant distributions of the fourth central moments of e, (2.81). This shows that farm return distribution is asymmetric, in that we found lower values (more than 50%) are concentrated on the left of the mean, with extreme values to the right. Deviations from normality would imply a movement away from the mean-variance framework, and the inclusion of higher moments of the distribution into risk analysis.

4.1 Impacts of CSA Practices on Risk Exposure

Table 5 presents the coefficients and standard errors of the multinomial treatment effects (MTE) model of the mean, variance, skewness and kurtosis functions. MTE is a treatment effects model to study the effect of multinomial treatment on a non-negative integer outcome (Deb and Trivedi 2006). With MTE, we address the impact of the adoption of alternative combinations of practices on variants of production risk. In all estimations, the baseline scenario is non-adoption of any of these practices. Most of the coefficients of the latent factors are significantly different from zero, confirming the presence of self-selection into choice of practices. This means that the correction for the sample selection bias was necessary.

[9] The Jarque–Bera test (JB) is a statistical goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. JB is defined as: JB = n/6 (S2 + 1/4K2), where n is the number of observations (or degrees of freedom in general); S is the sample skewness and K is the sample kurtosis.

Table 5. Parameter Estimates of the Central Moments of Net Crop Income Regression Using Multinomial Treatment Effect

	Mean		Variance		Skewness		Kurtosis	
Variables	Coefficients	SE	Coefficients	SE	Coefficients	SE	Coefficients	SE
Treatments								
$Va_1F_{e0}A_{w0}$	3,275.226***	852.687	1.957***	0.147	-2.305***	0.688	11.071***	2.904
Va0Fe1Aw0	3,108.431***	584.797	2.924***	0.089	-1.518***	0.431	21.481***	1.696
Va0Fe0Aw1	-1,604.343***	573.575	1.079***	0.076	1.224***	0.354	-0.993	1.512
Va1Fe1Aw0	6,055.811***	715.956	2.781***	0.094	-2.139***	0.436	13.419***	1.891
Va1Fe0Aw1	3,835.013***	979.735	0.188	0.167	-0.101	0.798	0.058	3.457
Va0Fe1Aw1	4,693.258***	579.713	0.415***	0.081	1.078***	0.368	5.978***	1.578
Va1Fe1Aw1	5,776.087***	610.122	0.422***	0.090	1.098***	0.425	5.853***	1.866
Household features								
Gender	619.238*	375.486	-0.007	0.072	-0.069	0.347	-0.354	1.521
ln (Age)	-2,050.352***	502.335	-0.112	0.096	-0.328	0.463	-1.337	2.030
ln (Familysize)	-172.726	388.943	-0.064	0.074	-0.327	0.359	-1.498	1.574
Resourceconstraints								
ln (Farmsize)	-1,954.819***	214.025	-0.074*	0.041	-0.315	0.197	-1.133	0.862
ln (Tlu)	346.999*	177.954	-0.018	0.034	-0.025	0.164	-0.190	0.721
ln (Asset)	427.269***	132.875	0.035	0.025	0.117	0.122	0.533	0.536
Information and market								
Teleph	921.134**	435.587						
ln (Disoutmkt)	-409.661*	209.339						
Shocks								
Rainindex	3,777.713***	3,777.713***	0.174*	0.095	0.753	0.458	2.512	2.010
Relygovt	1,020.211***	1,020.211***	0.133*	0.071	0.517	0.341	2.214	1.493
Farm features								
lnPlotdist	-183.293**	88.782	-0.023	0.017	-0.045	0.081	-0.163	0.357
Tenure	1,115.660***	326.451	0.160**	0.062	0.561*	0.299	2.236*	1.312
Higfert	2,310.300***	385.598	0.164**	0.074	0.606*	0.355	2.392	1.556
Medfert	1,876.788***	355.361	0.100	0.068	0.495	0.327	1.475	1.433
Flatslp	179.721	560.517	-0.191*	0.107	-0.825	0.518	-3.834*	2.270
Medslp	-359.781	564.886	-0.218**	0.108	-0.821	0.522	-3.621	2.288

	Mean		Variance		Skewness		Kurtosis	
Variables	Coefficients	SE	Coefficients	SE	Coefficients	SE	Coefficients	SE
Meddpth	101.285	381.765	0.111	0.073	0.486	0.352	2.564*	1.544
Manure	749.280***	266.856	-0.024	0.051	-0.156	0.244	-0.481	1.068
Cereal	-4,921.987***	368.890	-0.585***	0.070	-1.829***	0.337	-7.627***	1.475
Legume	-6,912.179***	444.924	-0.558***	0.085	-1.750***	0.409	-7.395***	1.795
Climate								
Rain_Stage1	-115.521	137.550	-0.021	0.026	-0.025	0.127	-0.077	0.558
Rain_Stage1_sq	-11.832	12.263	0.001	0.002	-0.003	0.011	-0.017	0.050
Rain_Stage2	266.856	169.341	0.171***	0.033	0.669***	0.157	2.667***	0.688
Rain_Stage2_sq	-1.001	17.827	-0.019***	0.003	-0.060***	0.016	-0.245***	0.072
Rain_Stage3	1,938.653***	128.780	0.231***	0.025	0.862***	0.119	3.024***	0.523
Rain_Stage3_sq	-155.249***	14.896	-0.017***	0.003	-0.066***	0.014	-0.233***	0.061
Rain_Stage1_cv	-0.782	1.145	-0.000	0.000	-0.000	0.001	-0.003	0.005
Rain_Stage2_cv	-13.881***	1.254	-0.001***	0.000	-0.004***	0.001	-0.014***	0.005
Rain_Stage3_cv	-5.461***	0.675	-0.000*	0.000	-0.001*	0.001	-0.004	0.003
Temp_Stage1	3,845.647***	341.216	0.490***	0.066	0.900***	0.317	1.818	1.388
Temp_Stage1_sq	-85.215***	7.035	-0.010***	0.001	-0.020***	0.007	-0.043	0.029
Temp_Stage2	504.116	616.759	-0.038	0.118	-0.953*	0.571	-6.948***	2.505
Temp_Stage2_sq	-11.959	13.010	0.001	0.002	0.019	0.012	0.134**	0.053
Temp_Stage3	-757.958	481.241	-0.003	0.092	-0.062	0.445	0.107	1.953
Temp_Stage3_sq	17.953*	10.261	-0.000	0.002	0.002	0.010	0.002	0.042
Year (2016)	-860.733***	267.176	0.131***	0.049	0.776***	0.234	3.311***	1.024
Constant	-20,940.730**	9,083.076	-4.090**	1.726	4.048	8.326	78.212**	36.499
/lnsigma	9.048***	0.019	0.53***	0.01	2.11***	0.01	3.59***	0.01
Lambda for $Va_1F_{e0}A_{w0}$	-1411.822***	540.103	-0.10*	0.07	-0.52**	0.25	-3.93***	0.68
Lambda for $Va_0F_{e1}A_{w0}$	950.122*	545.412	-0.01	0.06	-0.05	0.30	-2.31***	0.84
Lambda for $Va_0F_{e0}A_{w1}$	1472.628***	562.279	0.15***	0.05	0.61***	0.18	2.06***	0.70
Lambda for $Va_1F_{e1}A_{w0}$	-57.210	686.417	-0.08*	0.05	-0.44**	0.21	-0.16	0.86
Lambda for $Va_1F_{e0}A_{w1}$	-1047.416**	567.151	-0.001	0.05	-0.01	0.21	0.7	0.69
Lambda for $Va_0F_{e1}A_{w1}$	-125.558	553.212	0.05	0.05	0.09	0.20	-0.19	0.75
Lambda for $Va_1F_{e1}A_{w1}$	1500.772***	519.747	0.19***	0.04	0.81***	0.18	1.74**	0.82
Joint significance of selection instruments χ^2 (5)	49.72***		157.56		8.67		5.49	
Joint significance of time varying covariates χ^2 (10)	53.42***				13.27		13.34	
Joint significance of location variables χ^2 (4)	88.41***		10.73**		5.22		4.08	
Log likelihood			-25578.818		-37010.141		-47754.029	

*, ** and *** indicate that the difference between the two years is statistically significant at 10%, 5% and 1% level, respectively; Variables included but found non-significant are: Education; Credit; Plotindex; Depdpth; SE is Standard Error.

Estimates of the mean model with MTE are shown in column 1 of Table 5. The coefficients on adoption of improved crop varieties and inorganic fertilizer are positive and significant at the 1% level, indicating that both are positively associated with an increase in farm return. The MTE model shows that the coefficient on agricultural water management appeared to be negative, indicating agricultural water management negatively impacts the return. However, as expected, the MTE empirical strategy confirms that the coefficient of the interaction between any of these practices is positive, suggesting that combinations of any of the three practices cause greater farm returns. This is in agreement with the recent study by Teklewold et al. (2017) and supports the complementarity hypothesis that the simultaneous adoption of multiple practices could have an important role in sustaining the growth of returns in smallholder farms of Ethiopia.

Table 5 also reports estimation results of moment-based models based on MTE. These model specifications are the variance, skewness and kurtosis functions. The result indicates the sensitivity of the moments of farm returns with respect to the application of alternative combinations of CSA. In general, the three practices, both in isolation and in combination, have a positive impact upon the variance of farm returns. The result is in agreement with the production literature, which has shown that inputs such as fertilizer and modern seeds can be defined as risk-increasing inputs (Just and Pope, 1979; Paulson and Babcock, 2010; Cavatassi et al., 2011). However, the variance-increasing effect of improved crop varieties and inorganic fertilizer both in isolation and in combination is larger than the variance-increasing effect of agricultural water management. Even so, the variance-increasing effect of improved crop varieties and inorganic fertilizer is also lower when either or both of these inputs are combined with agricultural water management practices.

The estimation results on skewness and kurtosis of returns show that adaptation practices can affect the distribution of farm returns (beyond their effect on variance). Thus, there is a need to go beyond mean and variance in the analysis of production risk. Figure 2 illustrates kernel density plots of farm returns using combinations of practices, with all other explanatory variables held at sample mean. The plots show that farm income distribution is right-skewed and kurtotic and that the skewness and peakedness (kurtosis) of the distribution shifts due to the shifts in adoptions of CSA.

Column 3 of Table 5 shows that farm return skewness varies with the type of practices adopted. It is negative and statistically significant for the adoption of modern crop varieties and inorganic fertilizer when they are applied individually or when they are used in combination. In this case, the farm return distribution is concentrated on the right, with a longer tail on the left. The mean return is less than the median return, revealing a greater exposure to losses and down side risks. Agricultural water management affects farm return skewness and can reduce exposure to downside risks by increasing the return skewness. These effects are also notable when agricultural management practices are combined with the downside risk of increasing inputs, improved crop varieties and inorganic fertilizer. Thus in certain cases, agricultural water management practices can contribute to reducing exposure to downside risk, indicating that a combination of practices can help farmers reduce their exposure to unfavorable events and mitigate the effects of adverse weather shocks.

Adoption of improved crop variety and inorganic fertilizer either in isolation or in combination shows higher kurtosis, as evidence of fat tails where more of the variance is the result of infrequent extreme deviations. However, these two technologies exhibit lower kurtosis when they are combined with agricultural water management; therefore, a combination of practices also contributes to reducing rare events in the tails of the farm return distribution. This feature is also desirable. Although climate change may increase the likelihood of these rare events, combinations of practices can help mitigate their effects on farm returns.

As expected, the weather shocks variables played a significant role in explaining the mean and variations of farm returns. The moments of farm return distributions are subject to the amount and variability of precipitation and temperature and the variations account for the heterogeneous effects across the growth stages of crop development. The results reject the assumptions of additive weather effects and agree with the agronomic sciences that the effects of weather events are not equally likely across stages of the growing season. Accordingly, the result reveals that weather shocks such as intensity and variability of rainfall are particularly detrimental toward the middle of the growing stage, around the later vegetative, flowering and grain development phases. However, temperature effects do not extend over the same range of temperatures for all stages. Temperature has a significant role at the earlier stage of the crop development during germination and early vegetative. As suggested by the crop science literature, we found non-linear effects of temperature and rainfall on moments of farm return distributions. The positive first degree and negative second-degree terms for precipitation and temperature indicate an inverted U-shaped response to the mean, variance, skewness and kurtosis of farm returns, with decreases if precipitation and temperature are above certain thresholds.

We conducted a simultaneous test of equality of weather parameters across stages for both temperature and rainfall variables effects. An asymptotic statistical test rejects the hypothesis of equality of parameters across stages. Thus there is strong evidence that both the temperature and intensity and variability of precipitation response functions vary across the crop development stages. Thus the parameter estimate of amount of rainfall on mean and variance of farm returns during growing stage 3 is statistically different from the parameter estimates of amount of rainfall on mean and variance of farm returns in growth stage 2. The marginal effect of rainfall amount on mean farm return in stage 3 (455.00 Birr/ha) is significantly higher than the marginal effect of rainfall on farm return in stage 2. Similarly, the linear term of rainfall intensity in stage 2 and 3 shows rainfall is variance-increasing but downside risk-decreasing. The marginal effect of rainfall amount on variance and skewness of farm returns in stage 3 is significantly lower than that of the stage 2 rainfall amount. Hence, downside risk due to rainfall in stage 3 is higher than downside risk in stage 2. Likewise, amount of rainfall during stage 2 and 3 is positively and significantly associated with higher kurtosis, which is evidence of fat tails. However, further increasing rainfall leads to lower kurtosis, which contributes to reducing rare events in the tails of the farm return distribution; this can cause extreme gains or losses of returns. The average partial effect of precipitation on kurtosis in stage 3 is significantly higher than the effect in stage 2.

Figure 3 shows the heterogeneous effect of rainfall at different crop growth stages on moments of farm income with alternative combinations of CSA practices. For instance, for farmers who adopt fertilizer only, increasing rainfall in stage 1 is variance-decreasing, but it is variance-increasing in stage 2 and 3. But when agricultural water management is adopted together with fertilizer, the variance of farm returns also changes with an increasing amount of rainfall in each growing stage of the crop.

These observations about the heterogeneous effects of weather across crop growth stages have important implications for the analysis of climate change adaptation possibilities. This is mainly important for management of drought risks, specifically variance in the amount and timing of rainfall (Magan et al., 2011). It could be the case that informed farmers adjust timing (such as shifting sowing dates) and obtain flexibility in input use during the growing period (Fafchamp 2003), or implement appropriate interventions (such as agricultural water management practices) with a focus on the stages when the detrimental effect is significant (Van Noordwijk et al., 1994). The differential weather effect is also helpful for maximizing the quasi-option value of farming decisions depending on the information at the different development stage of the crops. This is the value obtained by waiting for additional information at different growth stages before making an irreversible investment (Arrow and Fisher 1974).

4.2 Impacts of CSA on Cost of Risk

As discussed above, adopting a combination of practices increases the right skewness of the farm return distribution and hence reduces downside risk. We also observed the significant effect of weather variables (precipitation and temperature) at different growth stages on skewness as well as on kurtosis of farm return distributions. This means that a change in skewness is most likely accompanied by a change in the kurtosis (Awondo et al., 2017). Therefore, we jointly consider both skewness and kurtosis to assess the effect on the risk premium of adoption of a combination of CSA practices, together with weather variables, to be able to properly show the net effect of adoption and weather variables.

Table 6 reports the predicted values of absolute risk aversion, downside risk aversion, and the relative risk premium. The result indicates that the predicted farm mean values of absolute risk aversion (AR) range from 0.28 to 0.64, with a sample mean of 0.45, and this is significantly different from zero. Binswanger (1980) estimated that the risk aversion coefficient in agriculture varied from 0 to over 7.5. This provides statistical evidence that the average farmers in the study areas exhibit Arrow–Pratt risk aversion; that is, they are willing to sacrifice a proportion of their expected income to avoid the risk associated with adoption of CSA in their production. However, while AR is high (0.64) for farmers who don’t adopt any of the CSA practices, it is significantly lower on average for farmers who do adopt the combination of all three practices. Thus, adopters of a combination of practices exhibit lower aversion to risk than farmer who adopt none of the practices. According to Table 6, the results linked to the downside risk (or third and fourth moments) are positive and significantly different from zero for all farmers adopting any of the practices. This is a skewed kurtotic distribution where the effects at the tails might not cancel out, thus requiring consideration of the joint effect on both skewness and kurtosis to fully evaluate the effect on downside risk. This suggests that farmers do not adopt practices that offer potential gains but that also places them at risk of losses below some critical level. The DR coefficients for both skewness and kurtosis distribution are higher for farmers who don’t apply any of the three practices, but exhibit a sharp decline with the adoption of the combinations of all three practices.

Table 6. Estimates of risk attitudes and risk premiums by alternative combination of CSA

Items	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_1Fe_0Aw_1$	$Va_0Fe_1Aw_1$	$Va_1Fe_1Aw_1$	Overall
Absolute Risk Aversion (AR)	0.64	0.40	0.45	0.41	0.42	0.38	0.35	0.28	0.45
	(0.64)	(0.28	(0.31)	(0.28)	(0.47)	(0.37)	(0.27)	(0.26)	(0.43)
Downside Risk Aversion (DR)									
- Skewness component	1.10	0.32	0.40	0.33	0.53	0.38	0.26	0.20	0.52
	(2.64)	(0.41	(0.51)	(1.33)	(2.17)	(1.62)	(1.04)	(0.76)	(1.71)
- Kurtosis component	3.71	0.40	0.55	0.72	1.79	1.12	0.52	0.39	1.45
	(17.53)	(0.72	(1.05)	(11.11)	(17.66)	(10.30)	(7.48)	(3.06)	(11.87)
Risk Premium	2525.22	4737.54	4067.77	975.49	2122.20	996.88	1155.93	1043.69	2084.11
	(6276.19)	(7818.29)	(6894.79)	(2615.40)	(6125.78)	(3851.65)	(3342.28)	(4620.01)	(5392.19)
Relative Risk Premium	23.41	30.54	33.19	8.79	14.83	7.24	8.52	6.39	0.17
	(0.58)	(0.50)	(0.56)	(0.24)	(0.43)	(0.28)	(0.25)	(0.28)	(0.44)
- Variance share	17.54	10.13	6.64	7.73	15.00	15.09	9.03	11.88	11.43
	(18.45)	(14.06)	(9.46)	(9.83)	(15.03)	(14.75)	(9.95)	(11.05)	(13.84)
- Skewness share	16.30	15.59	13.33	15.46	16.10	17.18	15.38	17.43	15.59
	(6.64)	(7.65)	(7.24)	(6.39)	(6.46)	(5.99)	(6.22)	(5.51)	(6.62)
- Kurtosis share	66.16	74.28	80.03	76.81	68.89	67.73	75.59	70.69	72.97
	(24.17)	(21.06)	(16.10)	(15.72)	(20.71)	(20.08)	(15.61)	(15.98)	(19.52)

Our model can also provide a basis for evaluating the welfare implications of risk for smallholder farmers. The implicit cost of risk with the adoption of alternative combinations of CSA can be measured by the relative risk premium, which represents the percentage of farm income that the farmer is willing to pay to avoid taking additional risks. Table 6 presents the relative risk premium for the choice of different combination of CSA. In our case, the average farmer is willing to pay 17 per cent of her mean farm return, i.e., Birr 2084 per hectare. This may confirm that preferences are closely related to risk aversion. We can see that the average farmers who don't adopt any of the CSA practices are willing to sacrifice about 23% of their farm income. The relative risk premium increases with the adoption of modern crop varieties (33%) and inorganic fertilizer (31%) but decreases with the adoption of agricultural water management practices (9%); in other words, modern crop varieties and fertilizer have a higher cost of risk, while agricultural water management has a lower cost of risk. The relative risk premium declines monotonically with the adoption of a combination of practices. These results indicate that, while risk and risk aversion can have a large negative effect on the welfare of farmers, the combination of practices can be a risk-decreasing strategy. Thus, agricultural water management practices as self-protection practices may encourage the use of risk-increasing but productivity-enhancing inputs (such as improved crop varieties and fertilizers).

Table 6 also depicts the decomposition of the risk premium into the three components: variance, skewness and kurtosis of farm income under alternative combination of CSA. This provides some insights on the relative importance of variance versus downside risk exposure (as captured by the third and fourth moments) in the evaluation of the cost of risk as well as the net effect of combinations of CSA on the risk premium resulting from the simultaneous change in skewness and kurtosis. With all variables held constant at the sample mean, while the cost of risk due to variance, skewness and kurtosis show similar trends with the adoption of different combinations, the kurtosis component exhibits the highest share of the risk. While the change in the variance and skewness components of the risk premium appear to be lower compared with the gross risk premium, failing to consider the risk associated with the change in kurtosis overstates the variance and skewness components of the cost of risk by about 20% and 50%, respectively. The result is consistent with Awondo et al., (2017), who found an overstated cost of risk associated with skewness when kurtosis is not considered, in their analysis of the private cost of risk for maize producers in Uganda.

5. Conclusions

In an attempt to enhance agricultural productivity and reduce risk, the use of multiple climate smart agricultural (CSA) practices that respond differently to the environment is common among farm households. This study investigates the hypothesis that CSA selection could be enhanced with the use of a quantitative portfolio model that incorporates crop yield variance and covariance between practices to minimize risks. In Ethiopia, agricultural water management (AWM) is an important adaptation strategy and potentially offers insurance against the risk associated with yield loss from changing climate and growing conditions. In this paper, we model the adoption of AWM in combination with modern crop varieties and inorganic fertilizer. Accordingly, we examine the net effect of bundling CSA – specifically, whether AWM is risk-increasing or risk-decreasing when it is combined with other yield-enhancing inputs. Two contributions of our study are (1) analyzing climatic requirements at different growth stages of the crop in a developing country context and (2) the role of portfolio of agricultural technologies and management options on production risk. We apply this analysis to a sample of smallholder agricultural households in the Nile Basin of Ethiopia.

In agreement with agronomic findings that moisture and temperature requirements vary by the stage of crop development, we strongly reject the assumption that weather shocks are merely additive across the growing cycle. We show, instead, that weather shocks are detrimental toward the middle of the season, around flowering time. This result implies that informed farmers may adjust the timing and level of inputs according to weather fluctuations throughout the growing season.

The implications are interesting for a few reasons. First, a number of stochastic biophysical factors such as extreme weather conditions of rainfall and temperature increase the risks inherent in smallholder farming. Second, there is considerable possibility for controlling the level of production risk through joint adoption of multiple agricultural practices that have different objectives in the production process. Third, the results can be helpful for designing adaptation possibilities through shifting growing seasons and promoting the appropriate intervention at the appropriate period of time.

References

Antle, J. M. (1983). Testing for stochastic structure of production: A flexible moment-based approach. *Journal of Business and Economic Statistics, 1(*3), 192–201.

Arrow, K., and Fisher, A. (1974). Environmental preservation, uncertainty, and irreversibility. *Quarterly Journal of Economics, 88,* 312–319.

Arslan, et al. (2013).

Asfaw, S., Di Battista, F., and Lipper, L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger. *Journal of African Economies, 25,* 637–669.

Awondo S. N., Ramirez, O. A., Colson, G. J., Fonsah, E. G., and Kostandini, G. (2017). Self-protection from weather risk using improved maize varieties or off-farm income and the propensity for insurance. *Agricultural Economics, 48,* 61–76.

Binswanger, H. (1980). Attitude towards risk: Experimental measurement in Rural India. *American Journal of Agricultural Economic, 62,* 395–407.

Boggess, W. G., Lynne, G. D., Jones, J. W., and Swaney, D. P. (1983). Risk-return assessment of irrigation decisions in humid regions. *Southern Journal of Agricultural Economics, 15,* 135–43.

Cavatassi, R., Lipper, L., and Narloch, U. (2011). Modern variety adoption and risk management in drought prone areas: Insights from the sorghum farmers of eastern Ethiopia. *Agricultural Economics, 42,* 279–292.

Deb, P., and Trivedi, P. K. (2006). Maximum simulated likelihood estimation of a negative binomial regression model with multinomial endogenous treatment. *Stata Journal, 6*, 246–255.

Dinku, T., Asefa, K., Hailemariam, K., and Connor, S. J. (2011). Improving availability, access and use of climate information. *World Meteorological Organization Bulletin, 60,* 80–86.

Erkossa, T., Haileslassie, A., and MacAlister, C. (2014). Enhancing farming system water productivity through alternative land use and water management in vertisol areas of Ethiopian Blue Nile Basin (Abay). *Agricultural Water Management, 132,* 120–128.

Fafchamps, M., and Shilpi, F. (2003). The spatial division of labor in Nepal. *The Journal of Development Studies, 39*(6), 23–66.

Fageria, N. K., Baligar, V. C., and Clark, R. B. (2006). Physiology of crop production. New York: The Haworth Press.

FAO. (2011). Climate change, water and food security. Food and Agriculture Organization of the United Nations. Rome.

Harris, et al. (2014).

Heckman, J. (1978). Dummy endogenous variables in a simultaneous equation system. *Econometrica, 46*(4), 931–959.

Just, R. E., and Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics, 61*, 276–284.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., and Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy. 42*, 400–411.

Kaufmann, R. K., and Snell, S. E. (1997). A biophysical model of corn yield: Integrating climatic and social determinants. *American Journal of Agricultural Economics, 79*(1), 178–190.

Kawasaki, K. and Uchida, S. (2016). Quality matters more than quantity: Asymmetric temperature effects on crop yield and quality grade. *American Journal of Agricultural Economics, 98*, 1195–1209.

Kim, K., and Chavas, P. J. (2003). Technological change and risk management: An application to the economics of corn production. *Agricultural Economics, 29*, 125–42.

Kim, K., Chavas, J-P., Barham, B., Foltz, J. (2012). Rice, irrigation and downside risk: A quantile analysis of risk exposure and mitigation on Korean farms. Paper presented at the Agricultural and Applied Economics Association analytical meeting, August 12-14, 2012, Seattle, Washington. Available at http://purl.umn.edu/124814.

Magnan N., Lybbert, T. J., Mrabet, R., and Fadlaoui, A. (2011). The quasi-option value of delayed input use under catastrophic drought-risks: The case of no-till in Morocco. *American Journal of Agricultural Economics, 93*, 498–504.

Mukasa, A. N. (2018). Technology adoption and risk exposure among smallholder farmers: Panel data evidence from Tanzania and Uganda. *World Development, 105*, 299–309.

Novella, N., and Thiaw, W. (2013). African rainfall climatology version 2 for famine early warning systems. *Journal of Applied Meteorology and Climatology, 52*, 588–606.

Ortiz-Bobea, A. (2013). Is weather really additive in agricultural production? Implications for climate change impacts. Discussion Paper. RFF DP 13–41.

Paulson, N. D., and Babcock, B. A. (2010). Readdressing the fertilizer problem. *Journal of Agricultural and Resource Economics, 35,* 368–384.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica*, *32*(1–2), 122–136.

Quisumbing, A. (2003). Food aid and child nutrition in rural Ethiopia. *World Development, 7*, 1309–1324.

Ramirez, O..A., Misra, S..K., Nelson, J. (2003). Efficient estimation of agriculturaltime series models with non-normal dependent variables. *American Journal of Agricultural Economics, 85*(4), 1029–1040.

Reynaud, A. (2009). Adaptation a` court et a` long terme de l'agriculture au risque de se´cheresse: une approche par couplage de mode`les biophysiques et e´conomiques. *Review of Agricultural and Environmental Studies, 90,* 121–154.

Ricome, A., Affholder, F., Gérard, F., Mullerd, B., Poeydebat, C., Quirion, P., and Sall, M. (2017). Are subsidies to weather-index insurance the best use of public funds? A bioeconomic farm model applied to the Senegalese groundnut basin. *Agricultural Systems, 156,* 149–176.

Schlenker, W., and Roberts, M. J. (2015). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences, 106*,(37) 15594–15598; https://doi.org/10.1073/pnas.0906865106.

Teklewold, H., Mekonnen, A., Köhlin, G., and Di Falco, S. (2017). Does adoption of multiple climate smart practices improve climate resilience of farmers? Empirical evidence from the Nile Basin of Ethiopia. *Climate Change Economics*, *8*(1). DOI: 10.1142/S2010007817500014

Van Noordwijk, M., Dijksterhuis, G. H., and Van Keulen,, H. (1994). Risk Management in crop production and fertilizer use with uncertain rainfall: How many eggs and which baskets. *Netherlands Journal of Agricultural Science, 42*, 249–269.

Yesuf, M., and Bluffstone, R. A. (2009). Poverty, risk aversion and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics, 91*, 1022–1037.