On Adaptation to Climate Change and Risk Exposure in the Nile Basin of Ethiopia

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Abstract. This study investigates the impact of climate change adaptation on farm households' downside risk exposure (e.g., risk of crop failure) in the Nile Basin of Ethiopia. The analysis relies on a moment-based specification of the stochastic production function. We estimate a simultaneous equations model with endogenous switching to account for the heterogeneity in the decision to adapt or not, and for unobservable characteristics of farmers and their farm. We find that (i) climate change adaptation *reduces* downside risk exposure, i.e., farm households that implemented climate change adaptation strategies get benefits in terms of a decrease in the risk of crop failure; (ii) farm households that did not adapt would benefit the most in terms of reduction in downside risk exposure from adaptation; and (iii) there are significant differences in downside risk exposure between farm households that did and those that did not adapt to climate change. The analysis also shows that the quasi-option value, that is the value of waiting to gather more information, plays a significant role in farm households' decision to adapt to climate change. Farmers that are better informed may value less the option to wait to adapt, and so are more likely to adapt than other farmers.

Keywords: adaptation, climate change, endogenous switching, Ethiopia, risk exposure, stochastic production function, skewness.

JEL classification: D80, Q18, Q54

1. Introduction

One consequence of climate change in sub Saharan Africa is that farmers will be more exposed to production risk. More erratic and scarce rainfall and higher temperature can imply that farmers will be facing a larger extent of uncertainty. A prime example is Ethiopia. Rainfall variability and associated drought have been major causes of food shortage and famine in Ethiopia. During the last forty years, Ethiopia has experienced many severe droughts leading to production levels that fell short of basic subsistence levels for many farm households (Relief Society of Tigray, REST and NORAGRIC at the Agricultural University of Norway 1995, p. 137). Harvest failure due to extreme weather events is the most important cause of risk-related hardship of Ethiopian rural households, with adverse effects on farm household consumption and welfare (Dercon 2004, 2005). Future prospects of climate change are likely to exacerbate these issues. The implementation of adaptation strategies is very important. Farmers may need to implement adaptation measures to invest in soil conservation measures in the attempt of keeping soil moisture. Alternatively they can plant trees to procure some shading on the soil or resort to water harvesting technologies. On the other hand, if the conditions become far too challenging, then farmers may see less of a scope for investment (i.e., prospect are too gloomy), and they might be forced out of agriculture and migrate with very important implications in terms of livelihoods.

This paper investigates whether the set of strategies (e.g., change crops, soil and water conservation) implemented in the field by farm households in response to long term changes in environmental conditions (i.e., temperature and rainfall) affect production risk exposure. In other words, are farm households that implemented climate change adaptation strategies getting benefits in terms of a reduction in risk exposure? Are there significant differences in risk exposure between farm households that did and those that did not adapt to climate change? Looking at the risk implications of adaptation to climate change is a novel contribution to the literature. There is a very large and growing body of literature assessing the impact of climate change in agriculture. This literature, however, focuses on the implications in terms of productivity of land values of climatic variables (e.g., Mendelsohn et al. 1994; Kurukulasuriya and Rosenthal 2003; Seo and Mendelsohn 2008; Deressa and Hassan 2010). To our knowledge the empirical assessment of the role of adaptation on risk exposure has not been investigated yet. We aim to fill this gap.

We define risk exposure in terms of downside risk (e.g., probability of crop failure). The analysis relies on a moment-based specification of the stochastic production function (Antle 1983; Antle and Goodger 1984). This method has been widely used in the context of risk management in agriculture (Just and Pope 1979; Kim and Chavas 2003; Koundouri et al. 2006; and Di Falco and Chavas 2009).The focus on crop failure seems natural in our setting. Avoiding crop failure is indeed the major preoccupation of farmers in Ethiopia. Moreover, since the variance does not distinguish between unexpected good and bad events, we consider the skewness in risk analysis, that is we approximate downside risk exposure by the third moment of the crop yield distribution. If the skewness of yield increases then it means that downside risk exposure decreases, that is the probability of crop failure decreases (Di Falco and Chavas 2009). This approach can thus capture the full extent of risk exposure. In addition, we assume that uncertainty comes from random climate variables, incomplete information, and from future profit flows, which depend on price and production uncertainty due to sudden changes in global markets (e.g., in agricultural commodities).

We investigate the effects of adaptation on risk exposure in an endogenous switching regression framework by using data from a survey undertaken in the Nile Basin of Ethiopia in 2005. The survey collected information on both farm households that did and did not adapt plus on a very large set of control variables. We take into account that the differences in risk exposure between those farm households that did and those that did not adapt to climate change could be due to unobserved heterogeneity. Indeed, not distinguishing between the casual effect of climate change adaptation and the effect of unobserved heterogeneity could lead to misleading policy implications. We account for the endogeneity of the adaptation decision by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood estimation. Finally, we build a counterfactual analysis, and compare the expected downside risk exposure under the actual and counterfactual cases that the farm household adapted or not to climate change. Treatment and heterogeneity effects are calculated to understand the differences in downside risk exposure between farm households that adapted and those that did not adapt.

Key findings of our analysis are (i) that adaptation to climate change *decreases* downside risk exposure, and so the risk of crop failure; (ii) that there are significant and non negligible differences in downside risk exposure between the farm households that adapted and those that did not adapt; (iii) that farm households that did not adapt would benefit the most in terms of reduction in risk exposure from adaptation; and (iv) that provision of information through radio, farmer-to-farmer extension, and extension officers is a key driver of adaptation. This implies that the quasi-option value, that is the value of waiting to gather more and better information, plays a significant role in farm households' decisions to adapt to climate change.

The next section presents a description of the study sites and survey instruments. Sections 3 and 4 outline the model and the estimation procedure used. Section 5 presents the results, and Section 6 concludes the paper by offering some final remarks.

2. Survey Design and Data Description

This study relies on a survey conducted on 1,000 farm households located within the Nile Basin of Ethiopia in 2005. The sampling frame considered traditional typology of agro-ecological zones in the country (namely, *Dega, Woina Dega, Kolla* and *Berha*), percent of cultivated land, degree of irrigation activity, average annual rainfall, rainfall variability, and vulnerability (number of food aid dependent population). The sampling frame selected the *woredas* (an administrative division equivalent to a district) in such a way that each class in the sample matched to the proportions for each class in the entire Nile basin. The procedure resulted in the inclusion of twenty *woredas*. Random sampling was then used in selecting fifty households from each *woreda*.

One of the survey instruments was in particular designed to capture farmers' perceptions and understanding on climate change, and their approaches on adaptation. Questions were included to investigate whether farmers have noticed changes in mean temperature and rainfall over the last two decades, and reasons for observed changes. About 90 percent of the sample perceived long term changes in mean temperature or/and rainfall over the last 20 years. About 68, 4, and 28 percent perceived mean temperature as increasing, decreasing and remaining the same over the last twenty years, respectively. Similarly, 18, 62 and 20 percent perceived mean annual rainfall increasing, declining and remaining the same over the last twenty years, respectively. Overall, increased temperature and declining rainfall are the predominant perceptions in our study sites.

Furthermore, some questions investigated whether farm households made some adjustments in their farming in response to long term changes in mean temperature and rainfall by adopting some particular strategies. We define the undertaken strategies as "adaptation strategies," and create the variable *adaptation* equal to 1 if a farm household adopted any strategy in response to long-term changes in mean temperature and rainfall, 0 otherwise. Changing crop varieties, adoption of soil and water conservation strategies, and tree planting were major forms of adaptation strategies followed by the farm households in our study sites. These adaptation strategies are mainly yield-related and account for more than 95 percent of the adaptation strategies followed by the farm households who actually undertook an adaptation strategy. The remaining adaptation strategies accounting for less than five percent were water harvesting, irrigation, non-yield related strategies such as migration, and shift in farming practice from crop production to livestock herding or other sectors. About 58 percent and 42 percent of the farm households had taken no adaptation strategies in response to long term shifts in temperature and rainfall, respectively. More than 90 percent of the respondents who took no adaptation strategy indicated lack of information, land, money, and shortages of labour, as major reasons for not undertaking any adaptation strategy. Lack of information is cited as the predominant reason by 40-50 percent of the households.

In addition, detailed production data were collected at different production stages (i.e., land preparation, planting, weeding, harvesting, and post harvest processing). The area is almost totally rainfed. Only 0.6 percent of the households are using irrigation water to grow their crops. Production input and output data were collected for two cropping seasons, i.e., *Meher* (long rainy season), and *Belg* (the short rainy season) at the plot level. However, many plots have two crops grown on them annually (one during each of the *Meher* and *Belg* seasons). The farming system in the survey sites is very traditional with plough and yolk (animals' draught power). Labor is the major input in the production process during land preparation, planting, and post harvest processing. Labor inputs were disaggregated as adult male's labor, adult female's labor, and children's labor. This approach of collecting data (both inputs and outputs) at different stages of production and at different levels of disaggregation should reduce cognitive burden on the side of the respondents, and increase the likelihood of retrieving a better retrospective data. The three forms of labor were aggregated as one labor input using adult equivalents. We employed the standard conversion factor in the literature on developing countries where an adult female and children labor are converted into adult male labor equivalent at 0.8 and 0.3 rates, respectively.

Finally, although a total of 48 annual crops were grown in the basin, the first five major annual crops (teff, maize, wheat, barley, and beans) cover 65 percent of the plots. These are also the crops that are the cornerstone of the local diet. We limit the estimation to these primary crops. The final sample includes twenty *woredas*, 941 farm households (i.e., on average about forty-seven farm households per *woreda*), and 2,807 plots (i.e., on average about three plots per farm household). The scale of the analysis is at the plot level. The basic descriptive statistics are presented in table 1, and the definition of the variables in table A1 of the appendix.

[TABLE 1 ABOUT HERE]

3. Adaptation to Climate Change and Risk Exposure

The climate change adaptation decision and its implications in terms of risk exposure can be modeled in the setting of a two stage framework.[1] In the first stage, we use a selection model for climate change adaptation where a representative risk adverse farm household *i* chooses to implement climate change adaptation strategies if the expected utility from final benefits if she adapts $U(\pi_1)$ is greater than the expected utility if she does not adapt $U(\pi_0)$, i.e.,

(1) $$E\left[U(\pi_1)\right]-E\left[U(\pi_0)\right]>0$$

where E is the expectation operator based on the subjective distribution of the uncertain variables facing the decision maker, and $U(.)$ is the von Neumann-Morgenstern utility function representing the farm household preferences under risk. In addition, we should consider the value that farm households assign to information. Farm households may decide to delay the adoption of climate change adaptation strategies in order to collect more information on climate change and on the adaptation strategies, for example, through extension officers, and farmer-to-farmer extension. This implies that the farm household chooses to adapt *iff*

(2) $$E\left[U(\pi_1)\right]-E\left[U(\pi_0)\right] \quad > \mathrm{I},$$

where $\mathrm{I} \geq 0$ represents the information value, which depends on the farm household's characteristics, the uncertainty on the adoption of new strategies, and the fixed costs of new investments (Koundouri et al. 2006).

[1] A more comprehensive model of climate change adaptation is provided by Mendelsohn (2000).

Let A* be the latent variable that captures the expected benefits from the adaptation choice with respect to not adapting. We specify the latent variable as

(3) $A_i^* = \mathbf{Z_i}\boldsymbol{\alpha} + \eta_i$ with $A_i = \begin{cases} 1 & if \quad A_i^* > 0 \\ 0 & otherwise \end{cases}$,

that is farm household *i* will choose to adapt ($A_i = 1$), through the implementation of some strategies in response to long term changes in mean temperature and rainfall, if A* > 0, and 0 otherwise. The vector **Z** represents variables that affect the expected benefits of adaptation. These factors can be classified in different groups. First, we consider the characteristics of the operating farm (e.g., soil fertility and erosion). For instance, farms characterized by more fertile soil might be less affected by climate change and therefore relatively less likely to implement adaptation strategies. Since extension services are one important means for farmers to gain information on this, access to extension (both government and farmer-to-farmer) can be used as a measure of access to information. Particularly relevant in this setting is that farmers received information on climate. Farmer head and farm household's characteristics (e.g., age, gender, education, marital status, if the farmer head has an off-farm job, and farm household size), and the presence of assets (e.g., machinery and animals) may in principle also affect the probability of adaptation. Experience is approximated by age and education.

In the second stage, we model the effect of adaptation on risk exposure by relying on a moment-based specification of the stochastic production function (Antle 1983; Antle and Goodger 1984) This is a very flexible device that has been largely used in agricultural economics to model the implication of weather risk and risk management (Just and Pope 1979; Kim and Chavas 2003; Koundouri et al. 2006; and Di Falco and Chavas 2009). Consider a risk averse farm household that produces output *y* using inputs **x** under risk through a production technology represented by a well-behaved (i.e., continuous and twice differentiable) stochastic production function $y = g(\mathbf{x}, \boldsymbol{\upsilon})$, where $\boldsymbol{\upsilon}$ is a vector of random variables representing risk, that is uncontrollable factors affecting output such as changes in temperature and rainfall, and extreme events.

Risk exposure is represented by the moments of the production function $g(\mathbf{x}, \boldsymbol{\upsilon})$. The moments are computed following Kim and Chavas (2003), and Di Falco and Chavas (2009). We consider the following econometric specification for $g(\mathbf{x}, \boldsymbol{\upsilon})$:

(4) $g(\mathbf{x}, \boldsymbol{\upsilon}) = f_1(\mathbf{x}, \boldsymbol{\gamma_1}) + u$

where $f_1(\mathbf{x}, \boldsymbol{\gamma_1}) \equiv E\left[g(\mathbf{x}, \boldsymbol{\upsilon})\right]$ is the mean of $g(\mathbf{x}, \boldsymbol{\upsilon})$, that is the first central moment, and $u = g(\mathbf{x}, \boldsymbol{\upsilon}) - f_1(\mathbf{x}, \boldsymbol{\gamma_1})$ is a random variable with mean zero whose distribution is exogenous to farmers' actions. The higher moments of $g(\mathbf{x}, \boldsymbol{\upsilon})$ are given by

(5) $E\left\{\left[g(\mathbf{x}, \boldsymbol{\upsilon}) - f_1(\mathbf{x}, \boldsymbol{\gamma_1})\right]^k | \mathbf{x}\right\} = f_k(\mathbf{x}, \boldsymbol{\gamma_k})$

for *k = 2, 3*. This implies that $f_2(\mathbf{x}, \boldsymbol{\gamma_2})$ is the second central moment, that is the variance, and $f_3(\mathbf{x}, \boldsymbol{\gamma_3})$ is the third central moment, that is the skewness. This approach provides a flexible representation of the impacts of inputs, (e.g., seeds, fertilizers, manure, and labour), assets (e.g., machinery and animals), and soil's characteristics (e.g., soil fertility and erosion level) on the distribution of output under production uncertainty. In this study we go beyond standard mean-variance analysis by considering the effects of skewness and downside risk exposure. An increase in skewness implies a reduction in downside risk exposure, which implies for example a reduction in the probability of crop failure. Reducing downside risk means decreasing the asymmetry (or skewness) of the risk distribution toward high outcome, holding both means and variance constant (Menezes, Geiss, and Tessler 1980).

The simplest approach to examine the impact of adaptation to climate change on farm households' downside risk exposure would be to include in the skewness equation a dummy variable equal to one if the farm-household adapted to climate change, and then, to apply ordinary least squares. This approach, however, might yield biased estimates because it assumes that adaptation to climate change is exogenously determined while it is potentially endogenous. The decision to adapt or not to climate change is voluntary and may be based on individual self-selection. Farmers that adapted may have systematically different characteristics from the farmers that did not adapt, and they may have decided to adapt based on expected benefits. Unobservable characteristics of farmers and their farm may affect both the adaptation decision and risk exposure, resulting in inconsistent estimates of the effect of adaptation on production risk and risk of crop failure. For example, if only the most skilled or motivated farmers choose to adapt and we fail to control for skills, then we will incur upward bias.

We account for the endogeneity of the adaptation decision by estimating a simultaneous equations model of climate change adaptation and risk exposure with endogenous switching by full information maximum likelihood (FIML). For the model to be identified it is important to use as exclusion restrictions, thus as selection instruments, not only those automatically generated by the nonlinearity of the selection model of adaptation (1) but also other variables that directly affect the selection variable but not the outcome variable. In our case study, we use as selection instruments the variables related to the information sources (e.g., government extension, farmer-to-farmer extension, information from radio, and, if received information in particular on climate), and the farmer head and farm household characteristics. We establish the admissibility of these instruments by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the adaptation decision but it will not affect the risk exposure among farm households that did not adapt. The information sources and the farmer head and farm household characteristics can be considered as valid selection instruments: they are statistically significant determinants of the decision to adapt or not to climate change (χ^2 = 27.33 and 93.16) but not of downside risk exposure among farm households that did not adapt (F-stat. = 1.09 and 1.49).[2]

To account for selection biases we adopt an endogenous switching regression model of downside risk exposure where farmers face two regimes (1) to adapt, and (2) not to adapt defined as follows:

(6a) Regime 1: $y_{1i} = \mathbf{X_{1i}\beta_1} + \varepsilon_{1i} \quad if \quad A_i = 1$

(6b) Regime 2: $y_{2i} = \mathbf{X_{2i}\beta_2} + \varepsilon_{2i} \quad if \quad A_i = 0$

where y_i is the third central moment $f_3(\mathbf{x}, \boldsymbol{\gamma}_3)$ of production function (4) in regimes 1 and 2, i.e., the skewness, and $\mathbf{X_i}$ represents a vector of inputs (e.g., seeds, fertilizers, manure, and labour), and of the soil's characteristics, and assets included in **Z**. The error terms in equations (3), (6a) and (6b) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix $\mathbf{\Sigma}$, i.e., $(\eta, \varepsilon_1, \varepsilon_2)' \sim N(\mathbf{0}, \mathbf{\Sigma})$

$$\text{with } \mathbf{\Sigma} = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix},$$

where σ_η^2 is the variance of the error term in the selection equation (1), which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor (Maddala 1983, p. 223), σ_1^2 and σ_2^2 are the variances of the error terms in the skewness functions (6a) and (6b), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i}.[3] Since y_{1i} and y_{2i} are not observed simultaneously the covariance between ε_{1i} and ε_{2i} is not defined (reported as dots in the covariance matrix $\mathbf{\Sigma}$, Maddala 1983, p. 224). An important implication of the error structure is that because the error term of the selection equation (1) η_i is correlated with the error terms of the skewness functions (6a) and (6b) (ε_{1i} and ε_{2i}), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are nonzero:

[2] The results are available from the authors upon request.

[3] For notational simplicity, the covariance matrix $\mathbf{\Sigma}$ does not reflect the clustering implemented in the empirical analysis.

$E\left[\varepsilon_{1i} \mid A_i = 1\right] = \sigma_{1\eta}\dfrac{\phi(\mathbf{Z_i\alpha})}{\Phi(\mathbf{Z_i\alpha})} = \sigma_{1\eta}\lambda_{1i}$, and $E\left[\varepsilon_{2i} \mid A_i = 0\right] = -\sigma_{2\eta}\dfrac{\phi(\mathbf{Z_i\alpha})}{1-\Phi(\mathbf{Z_i\alpha})} = \sigma_{2\eta}\lambda_{2i}$, where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_{1i} = \dfrac{\phi(\mathbf{Z_i\alpha})}{\Phi(\mathbf{Z_i\alpha})}$, and $\lambda_{2i} = -\dfrac{\phi(\mathbf{Z_i\alpha})}{1-\Phi(\mathbf{Z_i\alpha})}$. If the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to adapt and downside risk exposure are correlated, that is we find evidence of endogenous switching and reject the null hypothesis of the absence of sample selectivity bias. This model is defined as a "switching regression model with endogenous switching" (Maddala and Nelson 1975). An efficient method to estimate endogenous switching regression models is full information maximum likelihood estimation (Lee and Trost 1978).[4] The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is

(7) $$\ln L_i = \sum_{i=1}^{N} A_i \left[\ln\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \ln\sigma_1 + \ln\Phi(\theta_{1i}) \right] + (1-A_i)\left[\ln\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \ln\sigma_2 + \ln\left(1-\Phi(\theta_{2i})\right) \right],$$

where $\theta_{ji} = \dfrac{\left(\mathbf{Z_i\alpha} + \rho_j\varepsilon_{ji}/\sigma_j\right)}{\sqrt{1-\rho_j^2}}, \quad j = 1,2$, with ρ_j denoting the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of equations (6a) and (6b), respectively.

4. Conditional Expectations, Treatment and Heterogeneity Effects

The endogenous switching regression model can be used to compare the expected downside risk exposure of farm households that adapted (a) with respect to farm households that did not adapt (b), and to investigate the expected downside risk exposure in the counterfactual hypothetical cases (c) that the adapted farm households did not adapt, and (d) that the non-adapted farm household adapted. The conditional expectations for downside risk exposure in the four cases are defined as follows:

(8a) $E(y_{1i} \mid A_i = 1) = \mathbf{X_{1i}\beta_1} + \sigma_{1\eta}\lambda_{1i}$

(8b) $E(y_{2i} \mid A_i = 0) = \mathbf{X_{2i}\beta_2} + \sigma_{2\eta}\lambda_{2i}$

(8c) $E(y_{2i} \mid A_i = 1) = \mathbf{X_{1i}\beta_2} + \sigma_{2\eta}\lambda_{1i}$

(8d) $E(y_{1i} \mid A_i = 0) = \mathbf{X_{2i}\beta_1} + \sigma_{1\eta}\lambda_{2i}$.

Cases (a) and (b) represent the actual expectations observed in the sample. Cases (c) and (d) represent the counterfactual expected outcomes. In addition, following Heckman et al. (2001), we calculate the effect of the treatment "to adapt" on the treated (TT) as the difference between (a) and (c),

(9) $TT = E(y_{1i} \mid A_i = 1) - E(y_{2i} \mid A_i = 1) = \mathbf{X_{1i}(\beta_1 - \beta_2)} + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i}$,

which represents the effect of climate change adaptation on downside risk exposure of the farm households that actually adapted to climate change. Similarly, we calculate the effect of the treatment on the untreated (TU) for the farm households that actually did not adapt to climate change as the difference between (d) and (b),

(10) $TU = E(y_{1i} \mid A_i = 0) - E(y_{2i} \mid A_i = 0) = \mathbf{X_{2i}(\beta_1 - \beta_2)} + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}$.

We can use the expected outcomes described in (8a)-(8d) to calculate also the heterogeneity effects. For example, farm households that did not adapt may have been exposed to lower downside risk

[4] An alternative estimation method is the two-step procedure (see Maddala 1983, p. 224 for details). However, this method is less efficient than FIML, it requires some adjustments to derive consistent standard errors (Maddala 1983, p. 225), and it poorly performs in case of high multicollinearity between the covariates of the selection equation (3) and the covariates of the skewness equations (6a) and (6b) (Hartman 1991; Nelson 1984; and Nawata 1994).

than farm households that adapted regardless of the fact that they decided not to adapt but because of unobservable characteristics such as their abilities. We follow Carter and Milon (2005) and define as "the effect of base heterogeneity" for the group of farm households that decided to adapt as the difference between (a) and (d),

(11) $BH_1 = E(y_{1i} | A_i = 1) - E(y_{1i} | A_i = 0) = (\mathbf{X_{1i}} - \mathbf{X_{2i}})\boldsymbol{\beta_{1i}} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i})$.

Similarly for the group of farm households that decided not to adapt, "the effect of base heterogeneity" is the difference between (c) and (b),

(12) $BH_2 = E(y_{2i} | A_i = 1) - E(y_{2i} | A_i = 0) = (\mathbf{X_{1i}} - \mathbf{X_{2i}})\boldsymbol{\beta_{2i}} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i})$.

Finally, we investigate the "transitional heterogeneity" (TH), that is whether the effect of adapting to climate change is larger or smaller for the farm households that actually adapted to climate change or for the farm household that actually did not adapt in the counterfactual case that they did adapt, that is the difference between equations (9) and (10), i.e., (TT) and (TU).

5. Results

Table 2 reports the estimates of the endogenous switching regression model estimated by full information maximum likelihood with clustered standard errors at the *woreda* level.[5] The first column presents the estimation of downside risk exposure by ordinary least squares (OLS) with no switching and with a dummy variable equal to 1 if the farm household adapted to climate change, 0 otherwise. The second, third and fourth columns present, respectively, the estimated coefficients of selection equation (3) on adapting or not to climate change, and of downside risk exposure, which is represented by skewness functions (6a) and (6b) (i.e., the third central moments of production function (4) in regimes (1) and (2)), for farm households that did and did not adapt to climate change.[6]

[TABLE 2 ABOUT HERE]

The results of the estimation of equation (3) suggest that key drivers of farm households' decision to adopt some strategies in response to long term changes in mean temperature and rainfall are represented by the information sources farm households have access to, in particular the provision of climate information both from formal and informal institutions, (table 2, column (2)). Farm households that received information about future climate change, and had access to formal agricultural extension, farmer-to-farmer extension or the media are more likely to adapt. These positive effects may indicate that farmers that are better informed may value less the option to wait, and so are more likely to adapt than other farmers. This implies that waiting for gathering more and better information might have a positive value (Koundouri et al. 2006).

The question now is whether farm households that implemented climate change adaptation strategies got benefits in terms of a reduction in downside risk exposure, (e.g., a decrease in the probability of crop failure). The simplest approach to answer this question consists in estimating an OLS model of downside risk exposure that includes a dummy variable equal to 1 if the farm household adapted, 0 otherwise (table 2, column (1)). An increase in skewness implies a reduction in downside risk exposure. This approach would lead us to conclude that having adapted to climate change did not significantly reduce farm households' downside risk exposure (the coefficient of the dummy variable *adaptation* is positive but insignificant). This approach, however, assumes that adaptation to climate change is exogenously determined while it is a potentially endogenous variable. The estimation via OLS would yield biased and inconsistent estimates. In addition, OLS estimates do not explicitly account for

[5] We use the "movestay" command of STATA to estimate the endogenous switching regression model by FIML (Lokshin and Sajaia 2004).

[6] The estimated coefficients of the production function (4) in regimes (1) and (2) from which we derived the third central moments are available from the authors upon request.

potential structural differences between the skewness function of farm households that adapted to climate change and the skewness function of farm households that did not adapt. The estimates presented in the last two columns of table 2 account for the endogenous switching in the skewness function. Both the estimated coefficients of the correlation terms ρ_j are not significantly different from zero (table 2, bottom row). Although we could not have known it a priori, this implies that the hypothesis of absence of sample selectivity bias may not be rejected.

However, the differences in the coefficients of the skewness functions between the farm households that adapted and those that did not adapt illustrate the presence of heterogeneity in the sample (table 2, columns (3) and (4)). The skewness function of farm households that adapted to climate change is significantly different from the skewness function of farm households that did not adapt (at the 1 percent statistical level, F-stat. = 612.71). Among farm households that adapted to climate change inputs such as seeds and manure, and assets such as animals are significantly associated with an increase in the skewness, and so in a decrease in downside risk exposure, while infertile soils are associated with an increase in downside risk exposure. However, these factors do not significantly affect the downside risk exposure of farm households that did not adapt.

Table 3 presents the expected downside risk exposure under actual (cells (a) and (b)) and counterfactual conditions (cells (c) and (d)). Cells (a) and (b) represent the expected downside risk exposure observed in the sample if farm households adapted or not to climate change. The last column presents the treatment effects of adaptation on downside risk exposure. Our results show that adaptation to climate change significantly increases the skewness, that is decreases downside risk exposure, and so the probability of crop failure. In addition, we find that the transitional heterogeneity effect is negative, that is, farm households that did not adapt would have benefited the most in terms of reduction in risk exposure from adaptation. Finally, the last row, which adjusts for the potential heterogeneity in the sample, shows that farm households that actually did not adapt are less exposed to downside risk than the farm households that adapted in both counterfactual and actual conditions. This highlights that there are some important sources of heterogeneity that makes the non-adapters less exposed to downside risk than the adapters irrespective to the issue of climate change.

[TABLE 3 ABOUT HERE]

5. Conclusions

This paper investigated the implications of farm households' decision to adapt to climate on downside risk exposure. We used a moment-based approach that captures the third moment of a stochastic production function as measure of downside yield uncertainty. Then, we estimated a simultaneous equations model with endogenous switching to account for unobservable factors that influence downside risk exposure and the decision to adapt.

The first step of the analysis highlighted that access to information about climate change and extension services are key determinants of adaptation. They significantly increase the likelihood that farm households adapt to climate change. This finding is consistent with Koundouri et al. (2006) on irrigation technology adoption under production uncertainty. Farm households that are better informed may value less the option to wait, and so are more likely to adopt new technologies than other farmers. This implies that waiting for gathering more and better information might have a positive value, and the provision of information on climate change might reduce the quasi-option value associated with adaptation. Koundouri et al. (2006) conclude that "policy makers may use information provision to induce faster diffusion of adoption among farmers" (p. 659). They also emphasize that subsidies can be an alternative instrument to incentivise adoption and diffusion of new technology. However, subsidy policies may cause income transfers from other economic sectors with consequential welfare losses (Stoneman and David, 1986).

In addition, we can draw four main conclusions from the results of this study on the effects of climate change adaptation on downside risk exposure. First, climate change adaptation *reduces* downside risk exposure. Farm households that implemented climate change adaptation strategies get benefits in terms of a decrease in the risk of crop failure. Second, farm households that did not adapt would benefit the most in terms of reduction in downside risk exposure from adaptation. Third, there are significant differences in downside risk exposure between farm households that did and those that did not adapt to climate change. These differences represent sources of variation between the two groups that the estimation of an OLS model including a dummy variable for adapting or not to climate change cannot take into account. Fourth, there are some important sources of heterogeneity that makes the non-adapters less exposed to downside risk than the adapters irrespective to the issue of climate change.

These results are particularly important to design polices for effective adaptation strategies to cope with the potential impacts of climate change. Public policies can play an important role in helping farm households to adapt. The dissemination of climate change information and extension services are of paramount importance in determining the implementation of adaptation strategies, which could result in more food security for all farmers irrespective of their unobservable characteristics. The availability of information on climate change may raise farmers' awareness of the threats posed by the changing climatic conditions. Extension services provide an important source of information and education, for instance, on changing crops and specific soil conservation measures that can deliver food productivity gains. Future research will investigate the role of different adaptation strategies, and whether the beneficial effects of adaptation are sensitive to different rainfall areas.

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Appendix

Table A1. Variables Definition

Variable name	Definition
Dependent variables	
adaptation	dummy =1 if the farm household adapted to climate change, 0 otherwise
downside risk exposure	skewness $f_3(\mathbf{x}, \boldsymbol{\gamma}_3)$: third central moment of production function (4) / 10,000,000,000
Explanatory variables	
Soil characteristics	
high fertility	dummy =1 if the soil has a high level of fertility, 0 otherwise
infertile	dummy =1 if the soil is infertile, 0 otherwise
no erosion	dummy=1 if the soil has no erosion, 0 otherwise
severe erosion	dummy=1 if the soil has severe erosion, 0 otherwise
Assets	
machinery	dummy =1 if machineries are used, 0 otherwise
animals	dummy=1 if farm animal power is used, 0 otherwise
Inputs	
labour	labour use per hectare (adult days)
seeds	seeds use per hectare (kg)
fertilizers	fertilizers use per hectare (kg)
manure	manure use per hectare (kg)
Farmer head and farm household characteristics	
literacy	dummy =1 if the household head is literate, 0 otherwise
male	dummy =1 if the household head is male, 0 otherwise
married	dummy =1 if the household head is married, 0 otherwise
age	age of the household head
household size	household size
off-farm job	dummy =1 if the household head took a off-farm job, 0 otherwise
relatives	number of relatives in the *woreda*
Information sources	
government extension	dummy =1 if the household head got information/advice from government extension workers, 0 otherwise
farmer-to-farmer extension	dummy =1 if the household head got information/advice from farmer-to-farmer extension, 0 otherwise
radio information	dummy =1 if the household head got information from radio, 0 otherwise
climate information	dummy =1 if extension officers provided information on expected rainfall and temperature, 0 otherwise

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Table 1. Descriptive Statistics

Variable name	Total sample		Farm households that adapted		Farm households that did not adapt	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables						
adaptation	0.689	0.463	1.000	0.000	0.000	0.000
downside risk exposure	0.608	15.330	0.865	18.454	0.034	0.324
Explanatory variables						
Soil characteristics						
highly fertile	0.280	0.449	0.257	0.437	0.331	0.471
infertile	0.158	0.365	0.172	0.377	0.128	0.335
no erosion	0.484	0.500	0.472	0.499	0.510	0.500
severe erosion	0.104	0.305	0.114	0.318	0.081	0.274
Assets						
machinery	0.019	0.136	0.024	0.153	0.007	0.084
animals	0.874	0.332	0.887	0.317	0.842	0.365
Inputs						
labour	100.994	121.268	105.867	133.409	90.176	87.657
seeds	114.905	148.650	125.672	163.896	91.001	103.473
fertilizers	60.609	176.767	61.996	177.867	57.530	174.362
manure	198.148	831.347	254.560	951.670	72.758	438.123
Farmer head and farm household characteristics						
literacy	0.489	0.500	0.524	0.500	0.412	0.492
male	0.926	0.263	0.932	0.252	0.912	0.284
married	0.927	0.261	0.930	0.256	0.920	0.272
age	45.717	12.550	46.239	11.926	44.556	13.770
household size	6.597	2.190	6.760	2.138	6.234	2.260
off-farm job	0.250	0.433	0.285	0.452	0.170	0.376
relatives	16.464	43.630	19.534	51.284	9.457	13.259
Information sources						
government extension	0.609	0.488	0.761	0.426	0.269	0.444
farmer-to-farmer extension	0.516	0.500	0.660	0.474	0.196	0.397
radio information	0.307	0.461	0.382	0.486	0.139	0.346
climate information	0.422	0.494	0.563	0.496	0.110	0.313
Sample size	2,807		1,936		871	

Note: The sample size refers to the total number of plots. The final total sample includes 20 *woredas*, 941 farm households and 2,807 plots.

Table 2. Parameters Estimates of Climate Change Adaptation and Downside Risk Exposure

	(1)	(2)	(3)	(4)
Model	OLS	Endogenous Switching Regression[a]		
			Regime 1 (Adaptation = 1)	Regime 2 (Adaptation = 0)
Dependent Variable	Downside risk exposure	Adaptation 1/0	Downside risk exposure among farm households that adapted	Downside risk exposure among farm households that did not adapt
Adaptation 1/0	0.662			
	(0.389)			
Soil characteristics				
highly fertile	-0.470	-0.209	-0.639	-0.018
	(0.366)	(0.108)	(0.518)	(0.011)
infertile	-0.907*	0.090	-1.256**	-0.007
	(0.467)	(0.163)	(0.622)	(0.020)
no erosion	-0.181	0.065	-0.306	0.031
	(0.567)	(0.142)	(0.812)	(0.020)
severe erosion	-0.248	0.189	-0.368	0.015
	(0.751)	(0.135)	(1.057)	(0.039)
Assets				
machinery	-0.832*	0.534	-1.186*	-0.051
	(0.426)	(0.481)	(0.677)	(0.034)
animals	0.529	0.159	0.745*	0.025
	(0.329)	(0.189)	(0.398)	(0.021)
Inputs				
labour	-0.351		-0.468	0.013
	(0.326)		(0.406)	(0.025)
squared labour	0.025		0.031	-0.004
	(0.022)		(0.025)	(0.003)
seeds	0.689***		0.848***	-0.037
	(0.221)		(0.267)	(0.022)
squared seeds	-0.032**		-0.039**	0.008
	(0.014)		(0.016)	(0.005)
fertilizers	-0.087		-0.086	-0.001
	(0.090)		(0.122)	(0.011)
squared fertilizers	0.003		0.002	-0.000
	(0.002)		(0.003)	(0.0003)
manure	0.058*		0.051*	0.000
	(0.028)		(0.030)	(0.003)
squared manure	-0.001**		-0.001***	0.000
	(0.0003)		(0.000)	(0.0001)
Farmer head and farm household characteristics				
literacy		0.152		
		(0.152)		
male		-0.039		
		(0.329)		
married		-0.264		
		(0.295)		
age		0.013**		
		(0.006)		
household size		0.032		
		(0.035)		
off-farm job		0.343***		
		(0.124)		

relatives		0.009**		
		(0.004)		
Information sources				
government extension		0.592***		
		(0.113)		
farmer-to-farmer extension		0.538***		
		(0.143)		
radio information		0.500**		
		(0.203)		
climate information		0.625***		
		(0.166)		
constant	-0.275	-1.269	0.612	-0.017
	(0.358)	(0.376)	(1.129)	(0.022)
σ_i			18.170***	0.312***
			(6.730)	(0.082)
ρ_j			-0.048	-0.150
			(0.035)	(0.110)

Note: [a]Estimation by full information maximum likelihood at the plot level. Sample size: 2,807 plots. Robust standard errors clustered at the *woreda* level in parentheses. The dependent variable "downside risk exposure" refers to the third central moment $f_3(\mathbf{x}, \boldsymbol{\gamma}_3)$ (i.e., the skewness) of production function (4); σ_i denotes the square-root of the variance of the error terms ε_{ji} in the outcome equations (6a) and (6b), respectively; ρ_j denotes the correlation coefficient between the error term η_i of the selection equation (3) and the error term ε_{ji} of the outcome equations (6a) and (6b), respectively. The inputs coefficients have been multiplied by 100. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 3. Average Expected Downside Risk Exposure; Treatment and Heterogeneity Effects

	Decision Stage		
Sub-samples	To Adapt	Not to Adapt	Treatment Effects
Farm households that adapted	(a) 0.867 (0.023)	(c) -0.013 (0.003)	TT = 0.880*** (0.024)
Farm households that did not adapt	(d) 1.624 (0.031)	(b) 0.037 (0.001)	TU = 1.588*** (0.031)
Heterogeneity effects	BH_1 = -0.757 (0.041)	BH_2= -0.049*** (0.005)	TH = -0.708*** (0.041)

Note: (a) and (b) represent observed downside risk exposure, that is the third central moment $f_3(\mathbf{x}, \boldsymbol{\gamma}_3)$ of production function (4); (c) and (d) represent the counterfactual expected downside risk exposure. (a) $E(y_{1i} \mid A_i = 1)$; (b) $E(y_{2i} \mid A_i = 0)$; (c) $E(y_{2i} \mid A_i = 1)$; (d) $E(y_{1i} \mid A_i = 0)$ where

A_i = 1 if farm households adapted to climate change; A_i = 0 if farm households did not adapt;
y_{1i}: third central moment if farm households adapted;
y_{2i}: third central moment if farm households did not adapt;
TT: the effect of the treatment (i.e., adaptation) on the treated (i.e., farm households that adapted);
TU: the effect of the treatment (i.e., adaptation) on the untreated (i.e., farm households that did not adapt);
BH_i: the effect of base heterogeneity for farm households that adapted (i = 1), and did not adapt (i = 2);
TH = (TT - TU), i.e., transitional heterogeneity.

Standard errors in parentheses. *** Significant at the 1% level.