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Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation 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 in the Nile Basin of Ethiopia. The analysis relies on a moment-based specification of the stochastic production function. We use an empirical strategy that accounts for the heterogeneity in the decision on whether to adapt or not, and for unobservable characteristics of farmers and their farm. We find that (i) past adaptation to climate change adaptation reduces current downside risk exposure, and so the risk of crop failure; (ii) climate change adaptation would have been more beneficial to the non-adapters if they adapted, in terms of reduction in downside risk exposure; and (iii) climate change adaptation is a successful risk management strategy that makes the adapters' more resilient to climatic conditions.

Keywords: adaptation, climate change, downside risk exposure, environmental risk, Ethiopia. JEL classification: D80, Q18, Q54

1. INTRODUCTION

One consequence of climate change in sub Saharan Africa is that farmers will be more exposed to environmental risk. More erratic and scarce rainfall and higher temperature 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 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). Climate change exacerbates these issues. The implementation of adaptation strategies can, thus, be very important. Farmers, for instance, may invest in soil conservation measures in the attempt of retaining 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 production conditions become too challenging, then farmers may see less of a scope for action (i.e., prospects 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 having adapted to climate change, defined as having implemented a set of strategies (e.g., change crops, water harvesting, soil and water conservation) in response to long-term changes in environmental conditions (e.g., temperature and rainfall) affect current environmental risk exposure. In particular we pose the following questions: are farm households that in the past implemented climate change adaptation strategies getting benefits in terms of a reduction in current risk exposure? Are there significant differences

in risk exposure between farm households that did and those that did not adapt to climate change? Is climate change adaptation a successful risk management strategy that makes the adapters' more resilient to current environmental risk? Looking at the risk implications of adaptation to climate change is a novel contribution to the literature. There is, in fact, a very large and growing body of literature assessing the impact of climate change in agriculture. This literature, though, focuses on the implications of climatic variables on land values, revenues or productivity (e.g., Mendelsohn et al. 1994; Kurukulasuriya and Rosenthal 2003; Seo and Mendelsohn 2008; Deressa and Hassan 2010; Di Falco, Veronesi and Yesuf 2011). To our knowledge the empirical assessment of the role of past adaptation on risk exposure has not been investigated yet.

We define environmental risk exposure in terms of downside risk exposure measured by the skewness of yields. In an agricultural setting, downside risk is particularly relevant as it identifies the probability of crop failure. The analysis relies on a moment-based specification of the stochastic production function (Antle 1983; Antle and Goodger 1984; Chavas 2004). As mentioned, this method has been widely used in the context of risk management in agriculture (Just and Pope 1979; Kim and Chavas 2003; Koundouri, Nauges, and Tzouvelekas 2006). 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 focus on 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 a fuller extent of risk exposure.

We investigate the effects of adaptation on risk exposure in an endogenous switching regression framework by using data from a cross-sectional 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 of whether the farm household did or did not adapt 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 that (i) past adaptation to climate change *decreases* current downside risk exposure, and thereby the risk of crop failure; (ii) there are significant and non-negligible differences in risk exposure between adapters and non-adapters; (iii) farm households that did not adapt would benefit the most in terms of reduction in downside risk exposure from adaptation ; and (iv) the implementation of adaptation strategies is a successful risk management strategy that makes the adapters' more resilient to climatic conditions.

The paper proceeds as follows. Sections 2 and 3 describe the study sites and survey instruments. Section 4 outlines the model and the estimation procedure used. Section 5 presents

the results, and section 6 concludes by offering some final remarks and directions for future research.

2. BACKGROUND

Ethiopia's GDP is closely associated with the performance of its rainfed agriculture (Deressa and Hassan 2010). For instance, about 40 percent of national GDP, 90 percent of exports, and 85 percent of employment stem from the agricultural sector (Ministry of Finance and Economic Development 2007). The rainfed production environment is characterized by large extent of land degradation and very erratic and variable climate. Historically, rainfall variability and associated droughts have been major causes of food shortage and famine in Ethiopia. A recent mapping on vulnerability and poverty in Africa, indeed, listed Ethiopia as one of the countries most vulnerable to climate change with the least capacity to respond (Orindi et al. 2006; Stige et al. 2006).

The success of the agricultural sector is crucially determined by the productivity of small holder farm households. They account for about 95 percent of the national agricultural output, of which about 75 percent is consumed at the household level (World Bank 2006). With low diversified economy and reliance on rain-fed agriculture, Ethiopia's development prospects have been thus associated with climate. For instance, the World Bank (2006) reported that catastrophic hydrological events such as droughts and floods have reduced its economic growth by more than a third. The frequency of droughts has increased over the past few decades, especially in the lowlands (Lautze et al. 2003). A 2007 study, undertaken by the national meteorological service (NMS), highlights that annual minimum temperature has been increasing by about 0.37 degrees Celsius every 10 years over the past 55 years. Rainfall have been more

erratic with some areas becoming drier while other becoming relatively wetter. These findings point out that climatic variations have already happened in this part of the world. The prospect of further climate change can exacerbate this very difficult situation. Climate change is indeed projected to further reduce agricultural productivity (Rosenzweig and Parry 1994; Parry, Rosenzweig, and Livermore 2005; Cline 2007). Most of climate models converge in forecasting scenarios of increased temperatures for most of Ethiopia (Dinar et al. 2008).

3. SURVEY DESIGN AND DATA DESCRIPTION

Data are from 1,000 farm households located within the Nile Basin of Ethiopia in 2005. The survey 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*.

Importantly, one of the survey instruments was in particular designed to capture farmers' perceptions and understanding on climate change, and their approaches for 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.¹ Overall, increased temperature and declining rainfall are the predominant perceptions in our study sites. These perceptions do match with the existing evidence reported in the previous section.

¹ See Deressa et al. 2009.

Furthermore, some questions investigated whether farm households made some adjustments in their farming practices 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 and adoption of soil and water conservation strategies, 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.

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. 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. The three forms of labor were aggregated as one labor input using adult equivalents.²

Monthly rainfall and temperature data were collected from all the meteorological stations in the country for the period 1970-2000. Then, the *Thin Plate Spline* method of spatial

² 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.

interpolation was used to impute the household specific rainfall and temperature values using latitude, longitude, and elevation information of each household.³ This method is one of the most commonly used to create spatial climate data sets. Its strengths are that it is readily available, relatively easy to apply, and it accounts for spatially varying elevation relationships. However, it only simulates elevation relationship, and it has difficulty handling very sharp spatial gradients. This is typical of coastal areas. Given that our area of the study is characterized by significant terrain features, and no climatically important coastlines, the choice of the *Thin Spline method* is reasonable (for more details on the properties of this method in comparison to the other methods see Daly 2006).

The final sample includes twenty *woredas*, 941 farm households (i.e., on average about forty-seven farm households per *woreda*), and 2,801 plots (i.e., on average about three plots per farm household). The scale of the analysis is at the plot-level.⁴ 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]

4. MODEL OF CLIMATE CHANGE ADAPTATION AND RISK EXPOSURE

In this section we specify an econometric model of climate change adaptation and risk exposure. Particular functional forms are chosen to remain within the spirit of previous work in this area (Di Falco, Veronesi and Yesuf 2011). The simplest approach to examine the impact of

³ By definition, *Thin Plate Spline* is a physically based two-dimensional interpolation scheme for arbitrarily spaced tabulated data. The Spline surface represents a thin metal sheet that is constrained not to move at the grid points, which ensures that the generated rainfall and temperature data at the weather stations are exactly the same as data at the weather station sites that were used for the interpolation. In our case, the rainfall and temperature data at the weather stations are reproduced by the interpolation for those stations, which ensures the credibility of the method (see Wahba 1990).

⁴ 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 constitute the staple foods of the local diet. We limit the estimation to these primary crops.

climate change adaptation on farm households' downside risk exposure would be to include in the risk 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 on whether 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 chose 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 switching regression model of climate change adaptation and risk exposure with endogenous switching. In particular, we model the climate change adaptation decision and its implications in terms of risk exposure in the setting of a two stage framework.⁵ In the first stage, we use a selection model where a representative farm household chooses whether to adapt or not to adapt, while in the second stage we estimate conditional risk exposure functions accounting for the endogenous selection. Finally, we produce selection-corrected predictions of counterfactual downside risk exposure.

Stage I – Selection Model of Climate Change Adaptation

⁵ A more comprehensive model of climate change adaptation is provided by Mendelsohn (2000).

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 adapting $U(\pi_1)$ is greater than the expected utility from non-adapting $U(\pi_0)$, i.e., $E[U(\pi_1)] - E[U(\pi_0)] > 0$, where E is the expectation operator based on the subjective distribution of the uncertain variables facing the decision maker, and $U(\cdot)$ is the von Neumann-Morgenstern utility function representing the farm household's preferences under risk. 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

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

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 \mathbf{z} represents variables that affect the likelihood to adapt such as the characteristics of the operating farm (e.g., soil fertility and erosion); farm head and farm household's characteristics (e.g., age, gender, education, marital status, and farm household size); the presence of assets (e.g., machinery and animals); past climatic factors (e.g., rainfall and temperature); the experience of previous extreme events (e.g., droughts and floods); whether farmers received information on climate; government and farmer-to-farmer extensions, which can be used as measures of access to information about adaptation strategies. We approximate experience by age and education.

Stage II - Endogenous Switching Regression Model of Downside Risk Exposure

How do we measure risk exposure and its interplay with adaptation? In the second stage, we model the effect of adaptation on downside risk exposure by relying on a moment-based specification of the stochastic production function (Antle 1983; Antle and Goodger 1984; Chavas 2004). 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, Nauges, and Tzouvelekas 2006; Di Falco and Chavas 2009). Consider a risk averse farm household that produces output y using inputs \mathbf{x} under risk through a production technology represented by a well-behaved (i.e., continuous and twice differentiable) stochastic production function $y = g(\mathbf{x}, \mathbf{v})$, where \mathbf{v} is a vector of random variables representing risk, that is uncontrollable factors affecting output such as current changes in temperature and rainfall.

We assess the probability distribution of the stochastic production function $g(\mathbf{x}, \mathbf{v})$ by applying a moment-based approach (Antle 1983), that is risk exposure is represented by the moments of the production function $g(\mathbf{x}, \mathbf{v})$. We consider the following econometric specification for $g(\mathbf{x}, \mathbf{v})$:

$$(2) \quad g(\mathbf{x}, \mathbf{v}) = f_1(\mathbf{x}, \boldsymbol{\beta}_1) + u$$

where $f_1(\mathbf{x}, \boldsymbol{\beta}_1) \equiv E[g(\mathbf{x}, \mathbf{v})]$ is the mean of $g(\mathbf{x}, \mathbf{v})$, that is the first central moment, and

$u = g(\mathbf{x}, \mathbf{v}) - f_1(\mathbf{x}, \boldsymbol{\beta}_1)$ is a random variable with mean zero whose distribution is exogenous to farmers' actions. The higher moments of $g(\mathbf{x}, \mathbf{v})$ are given by

$$(3) \quad E\left\{[g(\mathbf{x}, \mathbf{v}) - f_1(\mathbf{x}, \boldsymbol{\beta}_1)]^k \mid \mathbf{x}\right\} = f_k(\mathbf{x}, \boldsymbol{\beta}_k)$$

for $k = 2, 3$. This implies that $f_2(\mathbf{x}, \boldsymbol{\beta}_2)$ is the second central moment, that is the variance, and

$f_3(\mathbf{x}, \boldsymbol{\beta}_3)$ is the third central moment, that is the skewness. This approach provides a flexible

representation of the impacts of past climatic factors (e.g., temperature and rainfall), inputs, (e.g., seeds, fertilizers, manure, and labour), assets (e.g., machinery and animals), farm household's 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, and we focus on the effects of skewness and downside risk exposure. The variance does not distinguish between unexpected good and bad events. 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).

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:

$$(4a) \text{ Regime 1: } y_{1i} = \mathbf{x}_{1i}\boldsymbol{\beta}_1 + \varepsilon_{1i} \quad \text{if } A_i = 1$$

$$(4b) \text{ Regime 2: } y_{2i} = \mathbf{x}_{2i}\boldsymbol{\beta}_2 + \varepsilon_{2i} \quad \text{if } A_i = 0$$

where y_i is the third central moment $f_3(\mathbf{x}, \boldsymbol{\beta}_3)$ of production function (2) in regimes 1 and 2, i.e., the skewness, and \mathbf{x}_i represents a vector of the past climatic factors, inputs, assets, farm head's, farm household's and soil's characteristics included in \mathbf{z} . In addition, the error terms in equations (1), (4a) and (4b) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix $\boldsymbol{\Sigma}$, i.e., $(\eta, \varepsilon_1, \varepsilon_2)' \sim N(\mathbf{0}, \boldsymbol{\Sigma})$

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

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 (4a) and (4b), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i} .⁶ 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 Σ , 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 (4a) and (4b) (ε_{1i} and ε_{2i}), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are nonzero:

$$E[\varepsilon_{1i} | A_i = 1] = \sigma_{1\eta} \frac{\phi(\mathbf{z}_i \boldsymbol{\alpha})}{\Phi(\mathbf{z}_i \boldsymbol{\alpha})} = \sigma_{1\eta} \lambda_{1i}, \text{ and } E[\varepsilon_{2i} | A_i = 0] = -\sigma_{2\eta} \frac{\phi(\mathbf{z}_i \boldsymbol{\alpha})}{1 - \Phi(\mathbf{z}_i \boldsymbol{\alpha})} = \sigma_{2\eta} \lambda_{2i}, \text{ where } \phi(\cdot) \text{ is}$$

the standard normal probability density function, $\Phi(\cdot)$ the standard normal cumulative density

function, and $\lambda_{1i} = \frac{\phi(\mathbf{z}_i \boldsymbol{\alpha})}{\Phi(\mathbf{z}_i \boldsymbol{\alpha})}$, and $\lambda_{2i} = -\frac{\phi(\mathbf{z}_i \boldsymbol{\alpha})}{1 - \Phi(\mathbf{z}_i \boldsymbol{\alpha})}$. 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).

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. Following Di Falco, Veronesi, and Yesuf (2011), we use as selection

⁶ For notational simplicity, the covariance matrix Σ does not reflect the clustering implemented in the empirical analysis.

instruments the variables related to the information sources (e.g., government extension, farmer-to-farmer extension, information from radio or the neighbourhood and, if received information in particular on climate), which enter in \mathbf{z} but not in \mathbf{x} . We establish the admissibility of these instruments by performing the simple falsification test by Di Falco, Veronesi, and Yesuf (2011): 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 can be considered as valid selection instruments: they are statistically significant determinants of the decision on whether to adapt or not to climate change ($\chi^2 = 47.84$) but not of downside risk exposure among farm households that did not adapt (F-stat. = 1.0).

Finally, we estimate Stage I and II simultaneously by full information maximum likelihood estimation (FIML) since this is a more efficient method to estimate endogenous switching regression models than a two-step procedure (Lee and Trost 1978).⁷ The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is

$$(5) \quad \ln L_i = \sum_{i=1}^N A_i \left[\ln \phi \left(\frac{\varepsilon_{1i}}{\sigma_1} \right) - \ln \sigma_1 + \ln \Phi(\theta_{1i}) \right] + (1 - A_i) \left[\ln \phi \left(\frac{\varepsilon_{2i}}{\sigma_2} \right) - \ln \sigma_2 + \ln (1 - \Phi(\theta_{2i})) \right],$$

where $\theta_{ji} = \frac{(\mathbf{z}_i \boldsymbol{\alpha} + \rho_j \varepsilon_{ji} / \sigma_j)}{\sqrt{1 - \rho_j^2}}, \quad j = 1, 2,$

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 (4a) and (4b), respectively.

4.1 COUNTERFACTUAL ANALYSIS

⁷ The two-step procedure (see Maddala 1983, p. 224 for details) not only it is less efficient than FIML but it also 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 (1) and the covariates of the skewness equations (4a) and (4b) (Hartman 1991; Nelson 1984; Nawata 1994).

The main objective of our study is to investigate the effect of having adapted to climate change on downside risk exposure, that is to estimate the treatment effect (Heckman, Tobias, and Vytlačil 2001). In absence of a self-selection problem, it would be appropriate to assign to the adapters a counterfactual skewness had they not adapted equal to the average skewness among non-adapters with the same observable characteristics. However, as already mentioned, unobserved heterogeneity in the propensity to adapt affecting also risk exposure creates a selection bias that cannot be ignored. The endogenous switching regression model just described can be applied to produce selection-corrected predictions of counterfactual downside risk exposure (i.e., skewness). It can be used to compare the expected downside risk exposure of farm households that adapted (a) relative to the non-adapters (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-adapters adapted. The conditional expectations for downside risk exposure in the four cases are defined as follows:

$$(6a) \ E(y_{1i} | A_i = 1) = \mathbf{x}_{1i}\boldsymbol{\beta}_1 + \sigma_{1\eta}\lambda_{1i}$$

$$(6b) \ E(y_{2i} | A_i = 0) = \mathbf{x}_{2i}\boldsymbol{\beta}_2 + \sigma_{2\eta}\lambda_{2i}$$

$$(6c) \ E(y_{2i} | A_i = 1) = \mathbf{x}_{1i}\boldsymbol{\beta}_2 + \sigma_{2\eta}\lambda_{1i}$$

$$(6d) \ E(y_{1i} | A_i = 0) = \mathbf{x}_{2i}\boldsymbol{\beta}_1 + \sigma_{1\eta}\lambda_{2i} .$$

Cases (6a) and (6b) represent the actual expectations observed in the sample. Cases (6c) and (6d) represent the counterfactual expected outcomes. In addition, following Heckman, Tobias, and Vytlačil (2001), we calculate the effect of the treatment “to adapt” on the treated (TT) as the difference between (6a) and (6c),

$$(7) \ TT = E(y_{1i} | A_i = 1) - E(y_{2i} | A_i = 1) = \mathbf{x}_{1i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} ,$$

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 (6d) and (6b),

$$(8) \quad TU = E(y_{1i} | A_i = 0) - E(y_{2i} | A_i = 0) = \mathbf{x}_{2i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}.$$

We can use the expected outcomes described in (6a)-(6d) to calculate also the heterogeneity effects. For example, farm households that did not adapt may have been exposed to lower downside risk 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 (6a) and (6d),

$$(9) \quad BH_1 = E(y_{1i} | A_i = 1) - E(y_{1i} | A_i = 0) = (\mathbf{x}_{1i} - \mathbf{x}_{2i})\boldsymbol{\beta}_{1i} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}).$$

Similarly for the group of farm households that decided not to adapt, “the effect of base heterogeneity” is the difference between (6c) and (6b),

$$(10) \quad BH_2 = E(y_{2i} | A_i = 1) - E(y_{2i} | A_i = 0) = (\mathbf{x}_{1i} - \mathbf{x}_{2i})\boldsymbol{\beta}_{2i} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}).$$

Finally, we investigate the “transitional heterogeneity” (TH), that is whether the effect of adapting to climate change is larger or smaller for the adapters or for the non-adapters in the counterfactual case that they did adapt, that is the difference between equations (7) and (8), 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.⁸ 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 (1) on climate change adaptation, and of downside risk exposure, which is represented by skewness functions (4a) and (4b) (i.e., the third central moments of production function (2) in regimes (1) and (2)), for adapters and non-adapters. Table A3 of the appendix shows the estimation of production function (2) in regimes (1) and (2) from which we derived the third central moments.

[TABLE 2 ABOUT HERE]

The estimation of equation (1) suggests 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, and the risk associated with the environmental characteristics of the farm. Access to government extension, media, and climate information increase the likelihood to adapt while farm households with highly fertile soils are less likely to adapt. In particular, rainfall in both rainy seasons displays an *U*-shape behaviour.⁹ In addition, we find that literacy have a positive significant effect on adaptation as well as having experienced a flood in the past. It may be argued that pooling different crops can

⁸ We use the “movestay” command of STATA to estimate the endogenous switching regression model by FIML (Lokshin and Sajaia 2004).

⁹ Di Falco, Veronesi, and Yesuf (2011) use current weather as a proxy for climate (while we use climatic variables such as past rainfall and mean temperature), and do not find an effect on adaptation.

induce some bias. There may be some underlying differences in their risk functions for instance. To control for this possible source of heterogeneity we included a set of dummy variables to capture the specificity of the different crops.

The question now is whether farm households that implemented climate change adaptation strategies experienced a reduction in downside risk exposure, (e.g., a decrease in the probability of crop failure). As described in the previous section, we assess the probability distribution of the stochastic production function by applying a moment-based approach. A simple approach to answer the aforementioned 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 the adaption significantly reduces farm households' downside risk exposure (the coefficient of the dummy variable *adaptation* is positive), although the effect is weak (significant at the 10 percent statistical level). This approach, however, assumes that adaptation to climate change is exogenously determined while it is a potentially an endogenous variable. The estimation via OLS would yield biased and inconsistent estimates. In addition, OLS estimates do not explicitly account for potential structural differences between the skewness functions of the adapters and non-adapters. 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). 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 the adapters is significantly different from the skewness function of the non-adapters (at the 1 percent statistical level, Chow test F-stat. = 1102.01). Among farm households that in the past adapted to climate change, inputs such as seeds and manure, assets such as animals, and being married 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 with the exception of seeds, which displays an *U*-shape behaviour. In addition, we find significant differences in the effect of the climatic factors on downside risk exposure. The non-adapters are significantly affected by the rainfall in both the short and long rainy seasons. The relationship between downside risk exposure and rainfall is *inverted U*-shaped. The adapters, instead, are not affected by the climatic factors.

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 of the adapters and non-adapters. 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. This finding can be explained by analyzing the last row of Table 3, which accounts for the potential heterogeneity in the sample. It shows that there is negative selection into choosing to adapt for the adapters, and positive selection into *not* choosing to adapt for the non-adapters. If the non-adapters had chosen to adapt, their risk

exposure would have been below that of the adapters. If the adapters had chosen not to adapt, their risk exposure would have been higher than that of the non-adapters. In short, non-adapters are less exposed to downside risk than the adapters both with adaptation and without adaptation.

[TABLE 3 ABOUT HERE]

6. CONCLUSIONS

This paper investigated the implications of farm households' past decision to adapt to climate change on current 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 the risk associated with the environmental characteristics of the farm such as soil fertility and access to information are key determinants of adaptation. These findings are consistent with Di Falco, Veronesi and Yesuf (2011) on climate change adaption and food productivity, and Koundouri, Nauges, and Tzouvelekas (2006) on irrigation technology adoption under production uncertainty. Koundouri, Nauges, and Tzouvelekas (2006) emphasize that 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. In addition, in this study we find that also education and past climatic factors significantly affect the adaptation decision. In particular, rainfall in both rainy seasons displays

an *U*-shape behaviour, being literate or having experienced a flood in the past have a positive effect on the likelihood to adapt.

We can draw four main conclusions from the results of this study on the effects of climate change adaptation on downside risk exposure. First, past climate change adaptation reduces current downside risk exposure. Farm households that implemented climate change adaptation strategies obtained benefits in terms of a decrease in the risk of crop failure. Second, adaptation would have been more beneficial to farm households that did not adapt if they adapted in terms of reduction in downside risk exposure. This larger positive effect of adaptation on downside risk exposure for the non-adapters is correlated with the fact that the non-adapters are less exposed to environmental risk than the adapters with or without adaptation. This leads us to the third finding. There are some important sources of heterogeneity and differences between adapters and non-adapters that make the non-adapters less exposed to downside risk than the adapters irrespective to the issue of 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. Last but not least, climate change adaptation is a successful risk management strategy that makes the adapters' more resilient to climatic conditions. The non-adapters are significantly affected by the rainfall in both the short and long rainy seasons while the adapters are not affected by climatic factors. Future research will investigate the role of different adaptation strategies, and whether the beneficial effects of adaptation are sensitive to different rainfall areas.

[TABLE A1 ABOUT HERE]

[TABLE A2 ABOUT HERE]

[TABLE A3 ABOUT HERE]

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Table 1. Descriptive Statistics

Variable name	Total sample		Adapters		Non-adapters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
<i>Dependent variables</i>						
adaptation	0.690	0.463	1.000	0.000	0.000	0.000
Skewness	0.593	14.877	0.845	17.903	0.034	0.320
<i>Explanatory variables</i>						
<i>Climatic factors</i>						
average temperature	18.523	2.228	17.945	1.991	19.809	2.190
Belg rainfall	257.064	146.275	224.635	135.490	329.284	143.617
Meher rainfall	960.439	293.511	910.282	304.337	1,072.136	231.788
<i>Crops varieties</i>						
barley	0.185	0.389	0.208	0.406	0.135	0.342
maize	0.199	0.399	0.194	0.396	0.211	0.408
teff	0.271	0.445	0.242	0.428	0.336	0.473
wheat	0.208	0.406	0.212	0.409	0.200	0.401
<i>Soil characteristics</i>						
highly fertile	0.280	0.449	0.257	0.437	0.333	0.472
infertile	0.158	0.365	0.172	0.378	0.127	0.333
no erosion	0.484	0.500	0.472	0.499	0.510	0.500
severe erosion	0.104	0.306	0.114	0.318	0.082	0.274
<i>Assets</i>						
machinery	0.019	0.136	0.024	0.153	0.007	0.085
animals	0.874	0.332	0.887	0.317	0.845	0.362
<i>Inputs</i>						
labor	101.088	121.383	105.912	133.503	90.344	87.743
seeds	115.181	148.732	125.867	163.948	91.385	103.552
fertilizers	60.760	176.962	62.092	177.988	57.795	174.720
manure	198.572	832.187	254.955	952.355	73.009	438.860
<i>Farm head and farm household characteristics</i>						
literacy	0.489	0.500	0.524	0.500	0.414	0.493
male	0.926	0.262	0.932	0.252	0.914	0.281
married	0.928	0.259	0.931	0.254	0.922	0.269
age	45.740	12.548	46.267	11.914	44.566	13.790
household size	6.603	2.189	6.765	2.136	6.243	2.261
relatives	16.494	43.682	19.561	51.321	9.473	13.287
flood	0.172	0.378	0.217	0.412	0.074	0.261
drought	0.443	0.497	0.565	0.496	0.171	0.376
<i>Information sources</i>						
government extension	0.609	0.488	0.761	0.427	0.270	0.444

farmer-to-farmer extension	0.516	0.500	0.659	0.474	0.197	0.398
radio information	0.307	0.461	0.382	0.486	0.139	0.347
neighborhood information	0.316	0.465	0.321	0.467	0.305	0.461
climate information	0.422	0.494	0.563	0.496	0.111	0.314
Sample size	2,801		1,933		868	

Note: The sample size refers to the total number of plots. The final total sample includes 20 *woredas*, 941 farm households, and 2,801 plots.

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

Exposure (Skewness)

	(1)	(2)	(3)	(4)
<i>Model</i>	OLS	Endogenous Switching Regression ^a		
			Regime 1 (Adaptation = 1)	Regime 2 (Adaptation = 0)
<i>Dependent Variable</i>	Skewness pool sample	Adaptation 1/0	Skewness adapters	Skewness non-adapters
adaptation 1/0	0.567* (0.316)			
<i>Climatic factors</i>				
average temperature	1.314 (0.769)	0.754 (0.552)	0.690 (1.287)	-0.188 (0.192)
squared average temperature	-0.033 (0.020)	-0.027* (0.015)	-0.011 (0.038)	0.007 (0.005)
Belg rainfall	-0.004 (0.007)	-0.014*** (0.003)	-0.001 (0.007)	0.003** (0.002)
squared Belg rainfall/1000	0.004 (0.011)	0.017*** (0.004)	0.001 (0.011)	-0.004* (0.002)
Meher rainfall	0.007 (0.005)	-0.009*** (0.002)	0.013 (0.009)	0.002*** (0.001)
squared Meher rainfall/1000	-0.003 (0.003)	0.005*** (0.001)	-0.007 (0.005)	-0.001*** (0.0004)
<i>Crop varieties</i>				
barley	2.059 (1.385)	-0.206** (0.082)	2.673 (1.794)	0.009 (0.020)
maize	0.662 (0.484)	0.013 (0.124)	0.751 (0.584)	-0.003 (0.043)
teff	0.054 (0.329)	-0.046 (0.094)	-0.060 (0.465)	0.001 (0.024)
wheat	-0.086 (0.405)	-0.174** (0.073)	-0.096 (0.557)	0.046 (0.030)
<i>Soil characteristics</i>				
highly fertile	-0.523 (0.430)	-0.167*** (0.062)	-0.707 (0.623)	0.023 (0.016)
infertile	-0.665** (0.282)	-0.085 (0.094)	-0.870** (0.400)	0.033 (0.021)
no erosion	-0.187	0.037	-0.209	0.009

	(0.612)	(0.091)	(0.871)	(0.026)
severe erosion	-0.400	-0.049	-0.373	0.031
	(0.896)	(0.087)	(1.170)	(0.043)
<i>Assets</i>				
machinery	-0.856**	0.877*	-0.879*	-0.065
	(0.349)	(0.488)	(0.491)	(0.106)
animals	0.332	0.166	0.490*	-0.033
	(0.207)	(0.175)	(0.261)	(0.042)
<i>Inputs</i>				
labor	-0.003		-0.005	-0.0001
	(0.003)		(0.003)	(0.0002)
squared labor/100	0.0002		0.000	-0.00001
	(0.0002)		(0.000)	(0.00002)
seeds	0.007***		0.009***	-0.0003**
	(0.001)		(0.002)	(0.0002)
squared seeds/100	-0.0003***		-0.0003***	0.0001*
	(0.0001)		(0.0002)	(0.00003)
fertilizers	-0.001		-0.002	-0.00002
	(0.001)		(0.002)	(0.0001)
squared fertilizers/100	0.00004		0.0001	0.0000001
	(0.00004)		(0.0001)	(0.000002)
manure	0.0005*		0.001*	-0.00001
	(0.0002)		(0.0003)	(0.00003)
squared manure/100	-0.000007***		-0.00001**	0.0000004
	(0.000002)		(0.000003)	(0.000001)
<i>Farm head and farm household characteristics</i>				
literacy	1.163	0.214**	1.540	-0.076**
	(0.803)	(0.086)	(0.980)	(0.035)
male	0.093	0.085	0.017	0.052
	(0.246)	(0.247)	(0.328)	(0.065)
married	0.563*	-0.224	0.949*	-0.075
	(0.325)	(0.350)	(0.528)	(0.101)
age	0.049	0.007	0.075	-0.002*
	(0.038)	(0.004)	(0.053)	(0.001)
household size	-0.124	0.035*	-0.187	-0.003
	(0.089)	(0.020)	(0.115)	(0.005)
relatives	-0.001	0.00001	-0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
flood	-1.218	0.197*	-1.499	-0.064
	(0.872)	(0.103)	(1.106)	(0.056)
drought	0.086	-0.055	-0.044	0.041
	(0.474)	(0.211)	(0.506)	(0.089)
<i>Information sources</i>				
government extension		0.266***		

		(0.084)		
farmer-to-farmer extension		0.047		
		(0.080)		
radio information		0.284***		
		(0.103)		
neighborhood information		0.043		
		(0.087)		
climate information		0.422***		
		(0.128)		
constant	-18.687*	1.406	-18.166	-0.223
	(9.574)	(5.009)	(11.212)	(1.430)
σ_i			17.796***	0.330***
			(6.554)	(0.093)
ρ_j			-0.038	-0.909
			(0.024)	(6.335)

Note: ^aEstimation by full information maximum likelihood at the plot-level. Sample size: 2,801 plots. Robust standard errors clustered at the *woreda* level in parentheses. The dependent variable “skewness” refers to the third central moment $f_3(\mathbf{x}, \boldsymbol{\gamma}_3)$ (i.e., downside risk exposure) of production function (2), and it has been rescaled; σ_i denotes the square-root of the variance of the error terms ε_{ji} in the outcome equations (4a) and (4b), respectively; ρ_j denotes the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of the outcome equations (4a) and (4b), respectively. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

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

<u>Sub-samples</u>	<u>Decision Stage</u>		<u>Treatment Effects</u>
	To Adapt	Not to Adapt	
Adapters	(a) 0.871 (0.045)	(c) -0.477 (0.003)	TT = 1.348*** (0.045)
Non-adapters	(d) 1.880 (0.059)	(b) 0.072 (0.002)	TU = 1.808*** (0.059)
<u>Heterogeneity effects</u>	BH ₁ = -1.009*** (0.080)	BH ₂ = -0.549*** (0.005)	TH = -0.460*** (0.079)

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

Appendix

Table A1. Variables Definition

Variable name	Definition
<i>Dependent variables</i>	
adaptation	dummy =1 if the farm household adapted to climate change, 0 otherwise
skewness	downside risk exposure: third central moment $f_3(\mathbf{x}, \boldsymbol{\beta}_3)$ of production function (2) / 10 milliards
<i>Explanatory variables</i>	
<i>Climatic factors</i>	
average temperature	average temperature (°C) 1970 - 2000
Belg rainfall	rainfall rate in Belg, short rainy season (mm) 1970 - 2000
Meher rainfall	rainfall rate in Meher, long rainy season (mm) 1970 - 2000
<i>Crop varieties</i>	
barley	dummy = 1 if the farm household grows barley, 0 otherwise
maize	dummy = 1 if the farm household grows maize, 0 otherwise
teff	dummy = 1 if the farm household grows teff, 0 otherwise
wheat	dummy = 1 if the farm household grows wheat, 0 otherwise
<i>Soil characteristics</i>	
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
<i>Assets</i>	
machinery	dummy =1 if machineries are used, 0 otherwise
animals	dummy=1 if farm animal power is used, 0 otherwise
<i>Inputs</i>	
labor	labor use per hectare (adult days)
seeds	seeds use per hectare (kg)
fertilizers	fertilizer use per hectare (kg)
manure	manure use per hectare (kg)
<i>Farm head and farm household characteristics</i>	
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
relatives	number of relatives in the <i>woreda</i>
flood	dummy =1 if the farm household experienced a flood during the last 5 years
drought	dummy =1 if the farm household experienced a drought during

<i>Information sources</i>	the last 5 years
government extension	dummy =1 if the household head received information/advice from government extension workers, 0 otherwise
farmer-to-farmer extension	dummy =1 if the household head received information/advice from farmer-to-farmer extension, 0 otherwise
radio information	dummy =1 if the household head received information from the radio, 0 otherwise
neighborhood information	dummy =1 if the household head received information from the neighborhood, 0 otherwise
climate information	dummy =1 if extension officers provided information on expected rainfall and temperature, 0 otherwise

Table A2. Parameter Estimates – Test on the Validity of the Selection Instruments

	Model 1	Model 2
	Adaptation 1/0	Skewness non-adapters
<i>Information sources</i>		
government extension	0.386** (0.152)	-0.044 (0.065)
farmer-to-farmer extension	0.125 (0.159)	0.060 (0.092)
radio information	0.345* (0.192)	-0.027 (0.041)
neighborhood information	0.061 (0.149)	-0.084* (0.042)
climate information	0.527** (0.213)	0.134 (0.102)
constant	1.409 (5.949)	-0.321 (0.734)
Wald test on information sources	$\chi^2 = 47.84^{***}$	F-stat. = 1.90
Sample size	2,801	868
Notes: Model 1: Probit model (Pseudo $R^2 = 0.432$); Model 2: ordinary least squares ($R^2 = 0.020$). Other covariates include climatic factors, crop varieties, soil characteristics, assets, inputs, farm head and farm household characteristics as specified in equations (1), (4a) and (4b). Estimation at the plot-level. Standard errors clustered at the <i>woreda</i> level in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.		

Table A3. Parameters Estimates of Production Function (2) in the two Regimes

Endogenous Switching Regression ^a		
	Regime 1 (Adaptation = 1)	Regime 2 (Adaptation = 0)
<i>Dependent Variable</i>	Quantity produced per hectare adapters	Quantity produced per hectare non-adapters
adaptation 1/0		
<i>Climatic factors</i>		
average temperature	-474.659* (261.062)	189.490 (286.768)
squared average temperature	12.789* (6.939)	-5.380 (7.123)
Belg rainfall	6.161** (2.431)	0.333 (1.330)
squared Belg rainfall/1000	-9.600*** (3.546)	-2.497 (1.989)
Meher rainfall	1.512 (0.947)	1.838** (0.825)
squared Meher rainfall/1000	-0.992* (0.558)	-0.877** (0.438)
<i>Crop varieties</i>		
barley	269.202** (110.226)	-4.850 (54.955)
maize	480.347*** (170.092)	227.171** (88.644)
teff	-28.664 (98.611)	-51.828 (66.151)
wheat	106.678 (73.138)	40.182 (52.621)
<i>Soil characteristics</i>		
highly fertile	133.226* (68.788)	60.286 (59.764)
infertile	-146.199*** (54.357)	-26.295 (60.463)
no erosion	-13.798 (77.029)	-16.575 (38.891)
severe erosion	54.826 (136.711)	-38.805 (78.550)
<i>Assets</i>		
machinery	-214.414	-68.547

	(146.472)	(93.006)
animals	183.958*	143.730**
	(100.788)	(66.212)
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<i>Inputs</i>		
labor	3.203***	3.118***
	(1.046)	(0.640)
squared labor/100	-0.128*	-0.338***
	(0.074)	(0.089)
seeds	2.172***	0.723
	(0.810)	(0.848)
squared seeds/100	0.059	0.253
	(0.036)	(0.174)
fertilizers	0.873***	1.046***
	(0.272)	(0.405)
squared fertilizers/100	-0.013**	-0.028***
	(0.006)	(0.010)
manure	0.188***	-0.009
	(0.060)	(0.129)
squared manure/100	-0.002**	0.004
	(0.001)	(0.003)
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<i>Farm head and farm household characteristics</i>		
literacy	-26.040	-110.746*
	(59.174)	(57.343)
male	221.095	340.548***
	(135.496)	(70.626)
married	-22.030	-223.548*
	(121.686)	(117.588)
age	-4.801**	-3.509*
	(2.262)	(1.869)
household size	-0.506	-0.317
	(17.371)	(10.433)
relatives	0.146	-1.234
	(0.184)	(2.147)
flood	-89.659	-166.854
	(91.153)	(113.357)
drought	-98.815	63.851
	(83.259)	(191.751)
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constant	3,473.906	-1,942.834
	(2,575.768)	(2,977.946)
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Note: ^aEstimation by full information maximum likelihood at the plot-level.

Sample size: 2,801 plots. Robust standard errors clustered at the *woreda* level in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.