Centre for Climate Change Economics and Policy

Grantham Research Institute on Climate Change and the Environment

Does adaptation to climate change provide food security? A micro-perspective from Ethiopia

Salvatore Di Falco, Marcella Veronesi and Mahmud Yesuf

May 2010

Centre for Climate Change Economics and Policy Working Paper No. 22

Grantham Research Institute on Climate Change and the Environment

Working Paper No. 19

The Grantham Foundation for the Protection of the Environment

ESRC Economic & Social Research Council

University of Leeds

The London School of Economics and Political Science

The Centre for Climate Change Economics and Policy (CCCEP) was established by the University of Leeds and the London School of Economics and Political Science in 2008 to advance public and private action on climate change through innovative, rigorous research. The Centre is funded by the UK Economic and Social Research Council and has five inter-linked research programmes:

1. Developing climate science and economics
2. Climate change governance for a new global deal
3. Adaptation to climate change and human development
4. Governments, markets and climate change mitigation
5. The Munich Re Programme - Evaluating the economics of climate risks and opportunities in the insurance sector

More information about the Centre for Climate Change Economics and Policy can be found at: http://www.cccep.ac.uk.

The Grantham Research Institute on Climate Change and the Environment was established by the London School of Economics and Political Science in 2008 to bring together international expertise on economics, finance, geography, the environment, international development and political economy to create a world-leading centre for policy-relevant research and training in climate change and the environment. The Institute is funded by the Grantham Foundation for the Protection of the Environment, and has five research programmes:

1. Use of climate science in decision-making
2. Mitigation of climate change (including the roles of carbon markets and low-carbon technologies)
3. Impacts of, and adaptation to, climate change, and its effects on development
4. Governance of climate change
5. Management of forests and ecosystems

More information about the Grantham Research Institute on Climate Change and the Environment can be found at: http://www.lse.ac.uk/grantham.

DOES ADAPTATION TO CLIMATE CHANGE PROVIDE FOOD SECURITY?

A MICRO-PERSPECTIVE FROM ETHIOPIA

Salvatore Di Falco

London School of Economics

Marcella Veronesi

Institute for Environmental Decisions, ETH Zurich

And

Mahmud Yesuf

Environment for Development Initiative, Ethiopia and Kenya

DOES ADAPTATION TO CLIMATE CHANGE PROVIDE FOOD SECURITY?

A MICRO-PERSPECTIVE FROM ETHIOPIA

Abstract. We examine the driving forces behind farmers' decisions to adapt to climate change, and the impact of adaptation on farmers' food production. We investigate whether there are differences in the food production functions of farm households that adapted and those that did not adapt. 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 compare the expected food production under the actual and counterfactual cases that the farm household adapted or not to climate change. We find that the group of farm households that adapted has systematically different characteristics than the group of farm households that did not adapt. The relationship between production and average temperature is *inverted U*-shaped for farm households that adapted, while it is *U*-shaped for farm households that did not adapt, and vice versa in the case of precipitation. We find that adaptation *increases* food production, however, the impact of adaptation on food production is smaller for the farm households that actually did adapt than for the farm households that did not adapt in the counterfactual case that they adapted.

Keywords: adaptation, climate change, endogenous switching, Ethiopia, food security, production, spatial data.

JEL classification: Q18, Q54

1. Introduction

At the core of the ongoing debate regarding the implications of climate change in sub-Saharan Africa there is the issue of food security. In this part of Africa, millions of small scale subsistence farmers farm land and produce food in extremely challenging conditions. The production environment is known to be characterized by a joint combination of low land productivity and harsh weather conditions (i.e., high average temperature, and scarce and erratic rainfall). These result in very low yields of food crops and food insecurity. With low diversified economies and reliance on rain-fed agriculture, sub-Saharan Africa's development prospects have been closely associated with climate. For instance, the World Bank reported that droughts and floods have reduced Ethiopia's economic growth by more than a third. Climate change is projected to further reduce food production (Rosenzweig and Parry, 1994; Parry *et al.*, 2005; Cline, 2007). A plethora of climate models converge in forecasting scenarios of increased temperatures for most of this area Dinar et al. 2008).

The fourth Intergovernmental Panel on Climate Change (2007) states that at lower latitude, in tropical dry areas, crop productivity is expected to decrease "for even small local temperature increases (1 – 2° C)." In many African countries access to food will be severely affected, "yields from rain fed agriculture could be reduced by up to 50% by 2020" (IPCC 2007, p.10). Given these gloomy prospects on food production, it is no surprise that the identification of both "climate-proofing" technologies and adaptation strategies are vital to support food crops yield. These strategies can indeed buffer against climate change and play a crucial role in reducing the food insecurity of farmers.

The links between climate change and food security have largely been explored focusing on the relation between climate variables and the productivity of food crops. Indeed, there is a large and growing body of literature that uses either agronomic models or *Ricardian* analysis to investigate the magnitude of these impacts (see Kurukulasuriya and Rosenthal, 2003; Seo and Mendelsohn, 2008). Agronomic models attempt to estimate directly, through crop models or statistical methods, the impacts of climate change on crop yields (Gommes *et al.*, 2009). Thus, they rely on experimental findings that indicate changes in yield of staple food crops such as wheat as a consequence of warming (e.g., Amthor, 2001; Fuhrer, 2003; Gregory *et al.*, 1999; Reilly *et al.*, 1994; Rosenzweig and Parry, 1994). Then, the results from the model are fed into behavioural models that simulate the impact of different agronomic practices on farm income or welfare. However, this approach does not consider the possible implications of farmers' adaptation thus overstating losses (Kurukulasuriya and Mendelsohn, 2008).

The *Ricardian* approach (pioneered by Mendelsohn *et al.*, 1994) purports to isolate, through econometric analysis of cross-sectional data, the effects of climate on farm income and land value, after controlling for other relevant explanatory variables (e.g., factor endowment, proximity to markets, etc.). The *Ricardian*[1] approach implicitly incorporates the possibility of the implementation of adaptation strategies by farmers. Since it is assumed that farms have been adapting optimally to climate in the observed past, the regression coefficients are estimating the marginal impacts on outputs of future temperature or precipitation changes already incorporating farmer's adaptive response. Thus, adaptation choices do not need to be modeled explicitly. One of the obvious shortcomings of this is that it is a black box that fails to identify the key adaptation strategies that reduce the implication of climate on food production. Disentangling the productive implications of adaptation to climate change is of paramount importance. Besides determining the impact of climatic variables on food

[1] This approach is technically convenient and widely adopted in a series of country level analyses. (see, Mendelsohn, 2000; Dinar et al 2008). However, global scale analysis can mask tremendous local differences.

production, it is necessary to understand the implications of adaptation "in the field." Most importantly, it is necessary to assess whether the farmers that actually did implement adaptation measures are indeed getting benefits in terms of an increase in the food crop production. This is very central if adaptation measures need to be put in place. Moreover, key assumption of the *Ricardian* is that land markets are working properly. Under this circumstance land prices will reflect the present discounted value of land rents into the infinite future (Deschenes and Greenstone, 2007). Properly working land markets may not be operating in areas of Africa where land property rights are not perfectly assigned. (i.e., large areas of Ethiopia are plagued by ill defined property rights and tenure insecurity).

This paper aims to contribute to the literature on climate change on agriculture by providing a micro perspective on both the impact of climate change on agriculture production, and the issue of adaptation and food security. We rely on a farm level survey of 1000 farms carried out in Ethiopia in 2005. The main target of the survey was to understand farmers' responses to climate change. The survey directly addressed to the farmers the questions about their perception of a long run change in key weather variables such as temperature and precipitation, and what they did to adapt to these changes. The sample contains both farms that did and did not adapt plus a very large set of control variables.

Ethiopia is a very interesting case study. A recent mapping on vulnerability and poverty in Africa (Orindi *et al.*, 2006; Stige *et al.*, 2006) listed Ethiopia as one of the countries most vulnerable to climate change with the least capacity to respond. The country's economy heavily relies upon the agricultural sector, which is mostly rainfed. (The agricultural sector accounts for about 40 percent of national GDP, 90 percent of exports, and 85 percent of employment.) Ethiopia's vulnerability is indeed largely due to climatic conditions. This has been demonstrated by the devastating effects of the various prolonged droughts in the 20^{th} century and recent flooding. The productive performance of the agricultural sector has been very low. For instance, agricultural GDP and per capita cereal production has been falling over the last 40 years with cereal yield stagnant at about 1.2 tons per hectare. Direct implication is that large areas of Ethiopia are plagued by food insecurity.

Ethiopian rural households face high weather variability. Significant spatial variations exist in agroecological conditions, including topography, soil type, temperature, and soil fertility (Hagos *et al.*, 1999). There is existing literature on the estimation of the impact of climate change on food production at country, regional and global scale (Pearce *et al.*, 1996; McCarthy *et al.*, 2001; Parry *et al.*, 2004; Stern, 2006). Insights from these studies are crucial in appreciating the extent of the problem and designing appropriate mitigation strategies at global or regional level. The aggregate nature of these studies, however, makes it very difficult to provide insights in terms of effective adaptation strategies at micro or farm household level.[2] Micro evidence on the impact of climatic change (particularly rainfall and temperature) and climate related adaptation measures on crop yield is very scanty.

Our study tries to fill the gap in the literature by examining the impact of key climatic variables on farmers' decisions to implement adaptation strategies (e.g., change crops, plant trees), and how the decision to adapt or not to adapt affects agricultural production. The role of information (provided by different sources) on climate change is also assessed. Besides farmers' socio-economic characteristics, we also address the role of assets such as machinery and animals on the adaptation decision. The use of climatic variables at the micro-level is also investigated. Lack of enough variation (spatial variation) on key climatic variables (precipitation and

[2] To the best of our knowledge, Temesgen (2006) is the only economic study that attempts to measure the impact of climate change on farm profit. This study applies the *Ricardian* approach where the cost of climate variability is imputed from capitalized land value. However, this study was conducted using sub-regional (agro-ecology) agricultural data, not farm household level data.

temperature) in cross sectional data is one major issue to conduct micro level studies on climate change. This can be particularly true in developing countries where one meteorological station is set to cover a wide geographic area. To partially fill this gap, this study employs the *Thin Plate Spline* method of spatial interpolation and imputes the household specific rainfall and temperature values using latitude, longitude, and elevation information of each farm household.[3]

In addition, we take into account that the differences in food production 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 (that is, for the heterogeneity in the decision to adapt or not to adapt to climate change and for unobservable characteristics of farmers and their farm) 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 food production 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 food production between farm households that adapted and those that did not adapt, and to anticipate the potential effects of changes in agricultural policy. To our knowledge, considering the existing literature, this is a novel exercise.

We find that there are significant and non negligible differences in food production between the farm households that adapted and those that did not adapt to climate change. We find that adaptation to climate change increases food production,

[3] See Wahba (1990) for details on the Thin Plate Spline method of climate data interpolation.

however, farmers who adapted tend to have a production above the average whether they adapt or they don't, and the impact of adaptation on production is smaller for the farm households that actually did adapt than for the farm households that did not adapt in the counterfactual case that they adapted. In addition, the relationship between production and average temperature and rainfall is of particular interest. We follow the current literature and include non linear terms (Mendelsohn *et al.*, 1994). We find evidence of an *inverted U*-shaped relationship between production and average temperature for farm households that adapted to climate change, and an *U*-shaped relationship for farm households that did not adapt. Different patterns across the two groups are also found when the climatic variable is precipitation.

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

2. Description of the Study Sites and Survey Instruments

The rural household survey was conducted on 1000 farm households located within the Nile Basin of Ethiopia. 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 *weredas* in such a way that each class in the sample matched to the proportions for each class in the entire Nile basin.[4] The procedure resulted in the inclusion of twenty villages. Random sampling was then used in selecting fifty households from each village.

[4] The *wereda* is an administrative division equivalent to a district.

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. The area is almost totally rain-fed. 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 plot level. However, many plots get bi-annual cropping pattern (grow both during *Meher* and *Belg* season). Thus, we estimated a production function only for *Meher* cropping season.

Detailed production data were collected at different production stages (i.e., land preparation, planting, weeding, harvesting 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. In this production function, the three forms of labor were aggregated as one labor input using adult equivalents.[5]

Monthly rainfall and temperature data were collected from all the meteorological stations in the country. Then, the Thin Plate Spline method of spatial interpolation was used to impute the household specific rainfall and temperature values using latitude, longitude, and elevation information of each household. By definition, Thin Plate Spline is a physically based 2D 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. So, in our case, the rainfall

[5] We employed the standard conversion factor in the literature in developing countries where an adult female and children labor are converted into adult male labor equivalent at 0.8 and 0.3 rates, respectively.

and temperature data at the weather stations will be reproduced by the interpolation for those stations and that ensures the credibility of the method (see Wahba, 1990 for details).

Finally, although a total of forty-eight 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 of the production function to these primary crops. The scale of the analysis is at the plot level. The final sample includes 940 farm households, that is 2,806 plots, with complete records for the variables of interest. The basic descriptive statistics are presented in Table 1, and the variables' definition in the appendix.

[TABLE 1 ABOUT HERE]

In addition, one of the survey instruments was designed to capture farmers' perceptions and understanding on climate change, and their approaches on adaptation. Questions were included to investigate whether the farmers have noticed changes in mean temperature and rainfall over the last two decades, and reasons for observed changes. 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 precipitations are the predominant perceptions in our study sites.

In response to long term perceived changes, farm households had undertaken a number of adaptation measures. Changing crop varieties, adoption of soil and water conservation measures, and tree planting were major forms of adaptation strategies followed by the farm households in our study sites. These adaptation measures are mainly yield-related and account for more than 95 percent of the adaptation measures followed by the farm households who actually undertook an adaptation measure. The remaining adaptation measures accounting for less than 5 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. On the other hand, about 58 percent and 42 percent of the farm households had taken no adaptation measures in response to long term shifts in temperature and precipitation, respectively. More than 90 percent of the respondents who took no adaptation measure indicated lack of information, land, money and shortages of labour, as major reasons for not undertaking any adaptation measure. Lack of information is cited as the predominant reason by 40-50 percent of the households.

3. Econometric Model and Estimation Procedure

We model food production via a representation of the production technology. We explored different functional forms. We present the most robust: a quadratic specification.[6] It has been argued that single output production functions do not capture the possibility of switching crops, and therefore the estimated impact of climatic variables on production is biased (Mendelsohn *et al.*, 1994). This can be particularly relevant when we look at a fairly specialized agriculture such as in the U.S.. However, in Ethiopia agriculture is characterised by highly diversified farms that grow a large number of different cereal crops. In addition, considering the total yields of cereal crops implicitly deals with the alternatives. The production environment constraints dramatically the production possibilities for farmers.

[6] Econometric results for other specifications are available from the authors upon request.

The simplest approach to examine the impact of adaptation to climate change on farm households' food production would be to include in the food production 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 to 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 the food production, resulting in inconsistent estimates of the effect of adaptation on food security. For example, if only the most skilled or motivated farmers choose to adapt and we fail to control for skills, then we will incur in an upward bias. We account for the endogeneity of the adaptation decision by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood (FIML).

We specify the selection equation for climate change adaptation as

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

that is farmers will choose to adapt ($A_i = 1$) if A* > 0, 0 otherwise, where A* represents the expected benefits of adapting with respect to not adapting, **Z** is a vector of variables that determine the decision to adapt or not to climate change, such as the farmer head's characteristics (e.g., age, gender, education, marital status, and if he has an off-farm job), the farm household's characteristics (e.g., farm household size, access to credit, soil fertility, and erosion level), the presence of assets (e.g., machinery and animals), climatic factors such as precipitation and average temperature, information about climate change, and formal and informal institutions such as formal agricultural extension, and farmer-to-farmer extension.[7]

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

(2a) Regime 1: $y_{1i} = \mathbf{X_{1i}\beta_1} + \varepsilon_{1i} \quad if \quad A_i = 1$

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

where y_i is the quantity produced per hectare in regimes 1 and 2, $\mathbf{X_i}$ represents a vector of inputs (e.g., seeds, fertilizers, manure, and labour), assets (e.g., machinery and animals), soil's characteristics (e.g., age, gender, education, marital status, farm size, soil fertility and erosion level), and climatic factors such as precipitation and temperature.[8]

Finally, the error terms are assumed to have a trivariate normal distribution, with zero mean and covariance matrix $\mathbf{\Sigma}$, i.e., $(\varepsilon_1, \varepsilon_2, \eta_1)' \sim N(\mathbf{0}, \mathbf{\Sigma})$ with

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

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), σ_1^2 and σ_2^2 are the variances of the error terms in the production functions (2a) and (2b), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i}. Since y_{1i} and y_{2i} are not observed simultaneously the covariance between ε_{1i} and ε_{2i} is not defined

[7] Experience is approximated by age and education.

[8] It could be argued that one could use land values or farm revenues as dependent variable and specify the analysis in terms of *Ricardian* analysis. It should be noted, however, that the implementation of the *Ricardian* analysis requires functioning markets (i.e., prices for land or products). This is not necessarily an available information in some developing countries. Markets for land may not work properly. Subsistence farms may operate in a context where food is produced for household consumption, and market prices for food crops are characterized by large variations.

(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 production functions (2a) and (2b) (ε_{1i} and ε_{2i}), the expected values of ε_{1i} and ε_{2i} condidional on the sample selection are nonzero:

$$E\left[\varepsilon_{1i} \mid A_i = 1\right] = \sigma_{1\eta}\frac{\phi(\mathbf{Z_i\alpha})}{\Phi(\mathbf{Z_i\alpha})} = \sigma_{1\eta}\lambda_{1i}, \text{ and } E\left[\varepsilon_{2i} \mid A_i = 0\right] = -\sigma_{2\eta}\frac{\phi(\mathbf{Z_i\alpha})}{1-\Phi(\mathbf{Z_i\alpha})} = \sigma_{2\eta}\lambda_{2i},$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_{1i} = \frac{\phi(\mathbf{Z_i\alpha})}{\Phi(\mathbf{Z_i\alpha})}$, and $\lambda_{2i} = -\frac{\phi(\mathbf{Z_i\alpha})}{1-\Phi(\mathbf{Z_i\alpha})}$. If the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to adapt and the quantity produced per hectare are correlated, that is we find evidence of endogenous switching and reject the null hypothesis of 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 by full information maximum likelihood estimation (Lee and Trost, 1978).[9] The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is

$$\text{(3)} \quad \ln L_i = \sum_{i=1}^{N} A_i \left[\ln\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \ln\sigma_1 + \ln\Phi(\theta_{1i}) \right] + (1-A_i)\left[\ln\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \ln\sigma_2 + \ln\left(1-\Phi(\theta_{2i})\right) \right],$$

9 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 shows poor performance in case of high multicollinearity between the covariates of the selection equation (1) and the covariates of the food production equations (2a) and (2b) (Hartman, 1991; Nelson, 1984; and Nawata, 1994).

where $\theta_{ji} = \frac{\left(\mathbf{Z_i \alpha} + \rho_j \varepsilon_{ji} / \sigma_j\right)}{\sqrt{1-\rho_j^2}}, \quad j = 1,2$, 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 (2a) and (2b), respectively.

In addition, for the model to be identified it is good practice in empirical analysis to use as exclusion restrictions not only those automatically generated by the nonlinearity of the selection regression but also other variables that directly affect the selection variable but not the outcome variables. The specification chosen for the food production equations (2a) and (2b), which follows common practice in the agricultural economics literature (see for example, Coelli and Battese, 1996 and Solis *et al.*, 2007, among others), allows us to use as exclusion restrictions the variables related to the information sources, and the farmer and farm household's characteristics.

4. Conditional Expectations, Treatment and Heterogeneity Effects

The aforementioned endogenous switching regression model can be used to compare the expected food production of the farm households that adapted (a) with respect to the farm households that did not adapt (b), and to investigate the expected food production 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 food production in the four cases are presented in Table 2 and defined as follows

(4a) $E(y_{1i} \mid A_i = 1) = \mathbf{X_{1i}\beta_1} + \sigma_{1\eta}\lambda_{1i}$

(4b) $E(y_{2i} \mid A_i = 0) = \mathbf{X_{2i}\beta_2} + \sigma_{2\eta}\lambda_{2i}$

(4c) $E(y_{2i} \mid A_i = 1) = \mathbf{X_{1i}\beta_2} + \sigma_{2\eta}\lambda_{1i}$

(4d) $E(y_{1i} \mid A_i = 0) = \mathbf{X_{2i}\beta_1} + \sigma_{1\eta}\lambda_{2i}$.

[TABLE 2 ABOUT HERE]

Cases (a) and (b) along the diagonal of Table 2 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),

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

which represents the effect of climate change adaptation on the food production 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),

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

We can use the expected outcomes described in (4a)-(4d) to calculate also the heterogeneity effects. For example, farm households that adapted may have produced more than farm households that did not adapt regardless of the fact that they decided to adapt but because of unobservable characteristics such as their skills. Adapting Carter and Milon (2005) to our case, we define as "the effect of base heterogeneity" for the group of farm households that decided to adapt as the difference between (a) and (d),

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

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

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

Finally, we investigate the "transitional heterogeneity" (TH), that is if 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 (5) and (6) (i.e., (TT) and (TU)).

5. Results

Table 3 reports the estimates of the endogenous switching regression model estimated by full information maximum likelihood.[10] The first column presents the estimation by ordinary least squares of the food production function with no switching and with a dummy variable equal to 1 if the farm household decided to adapt to climate change, 0 otherwise. The second, third and fourth columns present, respectively, the estimated coefficients of selection equation (1) on adapting or not to climate change, and of the food production functions (2a) and (2b) for farm households that did and did not adapt to climate change.[11]

[TABLE 3 ABOUT HERE]

The results of the estimation of equation (1) suggest that information about future climate change, and access to formal and informal institutions significantly increase the likelihood that farm households adapt (Table 3, column (2)). Farm households with access to credit are found to be more likely to adapt to climate change. The role of information also seems very important. We found that farmers that were informed about the implication of climate change (both via media and

[10] We use the "movestay" command of STATA to estimate the endogenous switching regression model by FIML (Lokshin and Sajaia, 2004).
[11] The estimated coefficients of the exclusion restrictions represented by the information sources and the farmer head and farm household' characteristics are jointly significantly different from zero (χ^2 (18) = 110.780; p-value = 0.000).

specific extension services) are more likely to adapt. More general extension services also play an important role in determining farmers' decisions to adapt. Both formal agricultural extension and farmer-to-farmer extension increase the probability of adaptation. In addition, farmers that have a job outside the farm or agricultural machinery are more likely to implement adaptation strategies.

Not surprisingly, climatic variables play a very important role in determining the probability of adaptation. Rainfall in the long rainy season displays an *inverted U*-shape behaviour. A similar pattern is identified when we look at the rainfall level during the *Belg* short rainy season. However, in the latter case the linear coefficient while positive is not statistically significant.

We now turn on the productive implications of adaptation. The simplest approach to investigate the effect of adaptation on food production consists in estimating an OLS model of food production that includes a dummy variable equal to 1 if the farm household adapted, 0 otherwise (Table 3, column (1)). This approach would lead us to conclude that farm households that adapted to climate change produce more than those that did not adapt, and in particular, about 129 Kg more per hectare *ceteris paribus* (the coefficient on the dummy variable *adaptation* is positive and significant at the 1 percent level). 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 potential structural differences between the production function of farmers who adapted to climate change and the production function of farmers that did not adapt.

The estimates presented in the last two columns of Table 3 account for the endogenous switching in the food production function**.** Both the estimated coefficients of the correlation terms ρ_j are not significantly different from zero (Table 3, 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 food production equation coefficients between the farm households that adapted and those that did not adapt illustrate the presence of heterogeneity in the sample (Table 3, columns (3) and (4)). The food production function of farm households that adapted to climate change is significantly different (at the 1 percent level) from the production function of the farm household that did not adapt. Consistent with predictions of economic theory, inputs such as seeds, fertilizers, manure and labour are significantly associated with an increase in the quantity produced per hectare by the farm households that adapted to climate change. However, mainly labour and fertilizers seem to significantly affect the food production of the farm households that did not adapt.

Another interesting difference between the farm households that did and those that did not adapt concerns the effect of temperature and precipitations on the quantity produced per hectare. The results of the impact of climate change on production are consistent with previous studies (Mendelshon *et al*., 1994). We find evidence of non linearity for both rainfall and temperature. Differently from the existing literature, we analyze the impact of climatic variables for the two different groups. When we distinguish between farmers that adapted versus farmers that did not adapt and we control for the different rainy season, we can unearth very interesting and distinct patterns. We find that the relationship between production and average temperature is *inverted U*-shaped for farm households that adapted to climate change, while it is *U*-shaped for farm households that did not adapt, and vice versa in the case of precipitations. This highlights the existence of a threshold in both groups.

Calculating the elasticities (evaluated at sample means) we find that the estimated impact of *Meher* rainfall is positive for both groups. However, the impact is stronger for the farmers that did not adapt (0.37%) with respect to the farmers that did adapt (0.24%). This seems to indicate that the implementation of the adaptation strategies successfully delivered relatively less reliance on the most important rainfall season, *Meher*. Results are different for rainfall during the short rainy season (*Belg* season). The coefficient estimates for the group of non adapters are statistically not significant.

The estimation of the impact of temperature reveals again the existence of non linearity and non negligible qualitative differences between the two groups. The impact of temperature on the group of adapters is positive. An increase of 1 percent in temperature is associated with an increment in production of 0.84 percent. The same increase in temperature has a quite large detrimental effect of food productivity of the non adapters (-0.44%). This indicates that the former group managed to support their productivity in the face of changing climate. The latter group, instead, are adversely affected by an increase average temperature.

Finally, Table 4 presents the expected quantity produced per hectare under actual and counterfactual conditions. Cells (a) and (b) represent the expected quantity produced observed in the sample. The expected quantity produced per hectare by farm households that adapted is about 1,134 Kg, while it is about 863 Kg for the group of farm households that did not adapt. This simple comparison, however, can be misleading and drive the researcher to conclude that on average the farm households that adapted produced about 271 Kg (that is 31 percent) more than the farm households that did not adapt.

[TABLE 4 ABOUT HERE]

The last column of Table 4 presents the treatment effects of adaptation on food production described in section 5. In the counterfactual case (c), farmers who actually adapted would have produced about 27 Kg (that is about 2.4 percent) more than if they did not adapt. In the counterfactual case (d) that farmers that did not adapt adapted, they would have produced about 230 Kg (that is about 27 percent) more than if they did not adapt. These results imply that adaptation to climate change increases food production, however, the transitional heterogeneity effect is negative, that is the effect is smaller for the farm household that actually did adapt with respect to those that did not adapt. In addition, the last row of Table 4, which adjusts for the potential heterogeneity in the sample, shows that farmers who decided to adapt tend to have benefits above the average whether they adapt or they do not, but they are better off adapting than not adapting.

6. Conclusions

The objectives of this paper were to analyse the driving forces behind farmers' decisions to adapt to climate change, and to investigate the productive implications of this decision. We used a unique database, where climatic information were disaggregated per season and available at the farm level to estimate a simultaneous equations model with endogenous switching to account for unobservable factors that influence food production and the decision to adapt or not to adapt.

The analysis of the determinants of adaptation highlighted very interesting results. Access to credit and information has a positive effect on the probability of adaptation. Developing credit markets allow farmers to make important investments (i.e., soil conservation measures) that can support farm productivity. In general, information on climate change and extension services also play an important role in determining farmers decisions to adapt. Both formal agricultural extension and farmer-to-farmer extension increase the probability of adaptation. In addition, rainfall displays an *inverted U*-shape behaviour, that is after a certain threshold level rain adaptation becomes less necessary.

Finally, we can draw three main conclusions from the results of this study on the effects of climate change adaptation on food security. First, the group of farm households that did adapt has systematically different characteristics than the group of farm households that did not adapt. 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. Second, adaptation to climate change increases food production, however, farmers who decided to adapt tend to have a production above the average whether they adapt or they do not. Last but not least, the impact of adaptation on food production is smaller for the farm households that actually did adapt than for the farm households that did not adapt in the counterfactual case that they adapted. These results are particularly important to design effective adaptation strategies to cope with the potential impacts of climate change.

[TABLE A1 ABOUT HERE]

References

Amthor, J. S. (2001): Effects of atmospheric CO2 concentration on wheat yield. Field Crops Res. 73:1–34.

Carter, D.W. and J.W. Milon (2005): "Price Knowledge in Household Demand for Utility Services," Land Economics 81(2):265-283.

Cline, W.R. (2007): *Global Warming and Agriculture. Impact Estimates by Country*. Washington D. C.: Center for Global Development and Peter G. Peterson Institute for International Economics.

Coelli, T. and G. Battese (1996): "Identification of Factors which Influence the Technical Inefficiency of Indian Farmers," Australian Journal of Agricultural Economics 40:103-128.

Dinar, A., R. Hassan, R. Mendelsohn, J. Benhin, and others (2008): *Climate Change and Agriculture in Africa: Impact Assessment and Adaptation Strategies*, London: EarthScan.

Fuhrer, J. (2003): "Agroecosystem Responses to Combinations of Elevated CO2, Ozone and Global Climate Change," Agric. Ecosyst. Environ. 97:1–20.

Gregory, P. J. et al. (2002): "Environmental Consequences of Alternative Practices for Intensifying Crop Production," Agric. Ecosyst. Environ. 88:279–290.

Hagos, F., J. Pender, and N. Gebreselassie (1999): "Land Degradation in the Highlands of Tigray and Strategies for Sustainable Land Management." Socioeconomic and Policy Research Working paper no. 25. Livestock Analysis Project, International Livestock Research Institute, Addis Ababa, Ethiopia.

Hartman, R.S. (1991): "A Monte Carlo Analysis of Alternative Estimators in Models Involving Selectivity," Journal of Business and Economic Statistics 9:41-49.

Heckman, J.J., J.L. Tobias and E.J. Vytlacil (2001): "Four Parameters of Interest in the Evaluation of Social Programs," Southern Economic Journal 68(2):210-233.

Intergovernmental Panel on Climate Change (IPCC) (2001): Climate Change 2001: The Scientific Basis. Contribution of the Working Group to the Third Assessment Report of the Intergovernmental Panel on Climate Change (eds. Hougthon, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell and C.A. Johnson). Cambridge: Cambridge University Press

Intergovernmental Panel on Climate Change (IPCC) (2007). Summary for Policymakers. Climate Change 2007: The Physical Science Basis. Working Group I Contribution to IPCC Fourth Assessment Report: Climate Change 2007, Geneva.

Kurukulasuriya, P., and S. Rosenthal (2003): “Climate Change and Agriculture: A Review of Impacts and Adaptations.” Climate Change Series 91. Environment Department Papers, World Bank, Washington, D.C

Lee, L.F. and R.P. Trost (1978): “Estimation of Some Limited Dependent Variable Models with Application to Housing Demand,” Journal of Econometrics 8:357-382.

Lokshin, M. and Z. Sajaia (2004): “Maximum Likelihood Estimation of Endogenous Switching Regression Models,” Stata Journal 4(3):282-289.

Maddala, G.S. (1983): Limited Dependent and Qualitative Variables in Econometrics. Cambridge, U.K.: Cambridge University Press.

Maddala, G.S. and F.D. Nelson (1975): “Switching Regression Models with Exogenous and Endogenous Switching,” Proceeding of the American Statistical Association (Business and Economics Section), pp. 423-426.

Mendelsohn, R., W. Nordhaus, and D. Shaw (1994): “The Impact of Global Warming on Agriculture: A Ricardian Analysis.” American Economic Review 84(4):753–771

Nawata, K. (1994): “Estimation of Sample Selection Bias Models by the Maximum Likelihood Estimator and Heckman’s Two-Step Estimator,” Economics Letters 45:33-40.

Nelson, F.D. (1984): “Efficiency of the Two-Step Estimator for Models with Endogenous Sample Selection,” Journal of Econometrics 24:181-196.

Parry, M., C. Rosenzweig, and M. Livermore (2005): “Climate Change, Global Food Supply and Risk of Hunger,” Phil. Trans. Royal. Soc. B, 360:2125-2138

Parry, M., C. Rosenzweig, A. Iglesias, M. Livermore, G. Fisher (2004): “Effects of Climate Change on Global Food Production under SRES Emissions and Socio-Economic Scenarios,” Global Environmental Change 14:53-67

Parry M.L., O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson (eds) (2007) Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA

Pearce, D, W. Cline, A Achanta, S Fankhauser, R Pachauri, R Tol, and P Vellinga (1996): “The Social Cost of Climate Change: Greenhouse Damage and the Benefits of Control,” in Bruce, J, H Lee, and E Haites (eds) Climate Change 1995: Economic and Social Dimensions of Climate Change. Cambridge: Cambridge University Press, pp. 179-224

Orindi V., Ochieng, A., Otiende, B. Bhadwal, S., Anantram, K. Nair, S., Kumar, V. and Kelkar U. (2006): “Mapping climate vulnerability and poverty in Africa”. In P.K. Thornton, P.G. Jones, T. Owiyo, R.L. Kruska, M. Herrero, P. Kristjanson, A. Notenbaert, N. Bekele and A. Omolo. Mapping Climate Vulnerability and Poverty in Africa, Report to the Department for

International Development, International Livestock Research Institute (ILRI), Nairobi.

Reilly, J. M. and D. Schimmelpfennig (1999): “Agricultural Impact Assessment, Vulnerability, and the Scope for Adaptation,” Climatic Change 43(4):745-788.

Rosenzweig, C., and M. L. Parry (1994): “Potential Impact of Climate Change on World Food Supply,” Nature, Vol. 367, pp. 133- 138

Seo, S.N. and R. Mendelsohn (2008): “Measuring Impacts and Adaptations to Climate Change: A Structural Ricardian Model of African Livestock Management,” Agricultural Economics 38(2):151-165.

Solis, D., B.E. Bravo Uretta, and R.E. Quiroga (2007): “Soil Conservation and Technical Efficiency Among Hillside Farmers in Central America: A Switching Regression Model,” The Australian Journal of Agricultural and Resource Economics 51:491-510.

Stern, N. (2007): *The Economics of Climate Change: The Stern Review*. Cambridge University Press

Stige, L.C., J. Stave, K.Chan, L. Ciannelli, N. Pattorelli, M. Glantz, H. Herren, N. Stenseth (2006): “The Effect of Climate Variation on Agro-Pastoral Production in Africa,” PNAS, 103: 3049-3053.

Temesgen T. (2006): “Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian Approach,” CEEPA discussion paper no. 25.

Wahba, G. (1990): *Spline Models for Observational Data*. Philadelphia: Society for Industrial and Applied Mathematics.

Appendix

Table A1 - Variables' Definition

Variable name	Definition
Dependent variables	
adaptation	dummy =1 if the farm household adapted to climate change, 0 otherwise
quantity produced per hectare	quantity produced per hectare (kg)
Explanatory variables	
Belg rainfall	precipitation rate in *Belg*, short rain season (mm)
Meher rainfall	precipitation rate in *Meher*, long rain season (mm)
average temperature	average temperature (^{o}C)
highly fertile	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
machinery	dummy =1 if machineries are used, 0 otherwise
animals	dummy=1 if farm animal power is used, 0 otherwise
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)
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 a village
access to credit	dummy =1 if the household has access to formal credit, 0 otherwise
gold	dummy =1 if the household has gold
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
neighborhood information	dummy =1 if the household head got information from the neighborhood, 0 otherwise
climate information	dummy =1 if extension officers provided information on expected rainfall and temperature, 0 otherwise

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	0	0	0
quantity produced per hectare	1,050.012	1,197.891	1,134.052	1,356.076	863.524	699.301
Explanatory variables						
Belg rainfall	323.132	160.666	307.796	150.141	357.036	177.223
Meher rainfall	1,111.298	294.790	1,145.737	284.731	1,035.163	302.434
average temperature	17.739	2.029	17.165	1.771	19.007	1.990
highly fertile	0.280	0.449	0.257	0.437	0.332	0.471
infertile	0.158	0.365	0.172	0.377	0.128	0.335
no erosion	0.482	0.500	0.470	0.499	0.508	0.500
severe erosion	0.104	0.305	0.114	0.318	0.081	0.273
machinery	0.019	0.136	0.024	0.152	0.007	0.084
animals	0.874	0.332	0.887	0.316	0.843	0.364
labour	100.972	121.284	105.837	133.437	90.176	87.657
seeds	114.875	148.668	125.633	163.930	91.001	103.473
fertilizers	60.587	176.739	62.028	177.907	57.398	174.184
manure	197.668	830.518	254.215	951.228	72.425	437.147
literacy	0.488	0.500	0.523	0.500	0.410	0.492
male	0.926	0.263	0.931	0.253	0.912	0.283
married	0.927	0.260	0.930	0.255	0.920	0.271
age	45.704	12.536	46.236	11.914	44.527	13.747
household size	6.597	2.190	6.763	2.138	6.230	2.258
off-farm job	0.249	0.433	0.286	0.452	0.169	0.375
relatives	16.420	43.540	19.489	51.215	9.448	13.216
access to credit	0.260	0.439	0.308	0.462	0.154	0.361
gold	0.378	0.485	0.454	0.498	0.208	0.406
government extension	0.608	0.488	0.761	0.426	0.269	0.444
farmer-to-farmer extension	0.515	0.500	0.660	0.474	0.196	0.397
radio information	0.306	0.461	0.383	0.486	0.138	0.345
neighborhood information	0.317	0.465	0.319	0.466	0.311	0.463
climate information	0.422	0.494	0.563	0.496	0.111	0.314

Table 2 - Conditional Expectations, Treatment and Heterogeneity Effects

Sub-samples	Decision Stage: To Adapt	Decision Stage: Not to Adapt	Treatment Effects
Farm households that adapted	(a) $E(y_{1i} \mid A_i = 1)$	(c) $E(y_{2i} \mid A_i = 1)$	TT
Farm households that did not adapt	(d) $E(y_{1i} \mid A_i = 0)$	(b) $E(y_{2i} \mid A_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Notes: (a) and (b) represent observed expected production quantities; (c) and (d) represent counterfactual expected production quantities.
A_i = 1 if farm households adapted to climate change; A_i = 0 if farm households did not adapt;
Y_{1i}: quantity produced if the farm households adapted;
Y_{2i}: quantity produced if the farm household 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.

Table 3 – Parameters Estimates of Climate Change Adaptation and Food Production Equations

	(1)	(2)	(3)	(4)
		Endogenous Switching Regression[a]		
Model	OLS		Adaptation = 1 (Farm households that adapted)	Adaptation = 0 (Farm households that did not adapt)
Dependent Variable	Quantity produced per hectare	Adaptation 1/0	Quantity produced per hectare	Quantity produced per hectare
Adaptation 1/0	128.827***			
	(38.564)			
Climatic factors				
Belg rainfall	-0.869	0.001	-2.122*	0.286
	(0.631)	(0.001)	(1.125)	(0.865)
squared Belg rainfall/1000	0.001	-0.004***	3.624**	-1.588
	(0.0009)	(0.002)	(1.672)	(1.334)
Meher rainfall	-0.249	0.003***	-2.059***	1.552***
	(0.431)	(0.001)	(0.721)	(0.572)
squared Meher rainfall/1000	0.0001	-0.001**	0.885***	-0.559**
	(0.0002)	(0.000)	(0.321)	(0.264)
average temperature	123.439	-1.074***	599.811***	-394.848**
	(115.237)	(0.235)	(163.427)	(178.579)
average temperature 2	-3.487	0.023***	-16.359***	9.862**
	(3.033)	(0.006)	(4.592)	(4.612)
Soil characteristics				
highly fertile	168.831***	-0.213***	207.874***	70.622
	(48.937)	(0.074)	(64.814)	(47.007)
infertile	-76.136	0.0004	-145.678*	1.062
	(52.020)	(0.094)	(75.520)	(67.872)
no erosion	24.687	0.122*	54.142	-17.956
	(40.235)	(0.070)	(58.284)	(45.757)
severe erosion	17.363	-0.010	62.780	-50.087
	(70.091)	(0.116)	(90.957)	(84.347)
Assets				
machinery	-131.841	0.822**	-148.538	-157.177
	(106.704)	(0.365)	(174.534)	(250.053)
animals	160.334***	0.007	173.922**	150.768**
	(39.554)	(0.094)	(86.903)	(60.208)
Inputs				
labour	3.017***		3.316***	3.866***
	(0.442)		(0.447)	(0.481)
squared labour /100	-0.120***		-0.127***	-0.431***
	(0.029)		(0.035)	(0.076)
seeds	1.952***		2.509***	-0.014
	(0.403)		(0.327)	(0.490)
squared seeds /100	0.069***		0.044**	0.349***
	(0.018)		(0.022)	(0.091)
fertilizers	0.683**		0.486*	0.752***
	(0.296)		(0.281)	(0.241)
squared fertilizers/100	-0.011*		-0.003	-0.021***
	(0.007)		(0.009)	(0.007)
manure	0.302***		0.281***	0.064
	(0.083)		(0.064)	(0.121)
squared manure /100	-0.003***		-0.003***	0.002
	(0.0007)		(0.001)	(0.003)
Farmer head and farm household characteristics				
literacy		0.097		
		(0.071)		

male		0.137 (0.158)		
married		-0.240 (0.168)		
age		0.007** (0.003)		
household size		0.053*** (0.016)		
off-farm job		0.226*** (0.083)		
relatives		0.004* (0.002)		
access to credit		0.246*** (0.080)		
gold		0.050 (0.076)		
Information sources				
government extension		0.465*** (0.080)		
farmer to farmer extension		0.410*** (0.081)		
radio information		0.335*** (0.088)		
neighborhood information		-0.099 (0.079)		
climate information		0.479*** (0.089)		
constant	-634.053 (1125.473)	8.884*** (2.247)	-3,852.883*** (1,354.133)	3,413.311* (1,752.811)
σ_i			1154.398 (18.602)	594.731 (14.191)
ρ_j			-0.039 (0.117)	-0.046 (0.094)

Notes: [a]Estimation by full information maximum likelihood.
Standard errors in parentheses. The number of observations is 2,806. σ_i denotes the square-root of the variance of the error terms ε_{ji} in the outcome equations (2a) and (2b), 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 (2a) and (2b), respectively. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 4 – Average Expected Production per Hectare; Treatment and Heterogeneity Effects

	Decision Stage		
Sub-samples	To Adapt	Not to Adapt	Treatment Effects
Farm households who adapted	(a) 1,134.056	(c) 1,107.508	TT = 26.547
Farm households who did not adapt	(d) 1,091.406	(b) 862.678	TU = 228.723
Heterogeneity effects	BH_1 = 42.65	BH_2= 244.83	TH = -202.176

See notes of Table 2.