Estimating the Impact of Climate Change on Agriculture in Low-Income Countries: Household Level Evidence from the Nile Basin, Ethiopia

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Abstract   This paper presents an empirical analysis of the impact of climate change on agriculture in a typical developing country. The economic implications of climate change are estimated by using both a farm productivity and a Ricardian framework. Data are drawn from about 1,000 farms producing cereal crops in the Nile Basin of Ethiopia. The thin plate spline method of spatial interpolation was used to predict household specific rainfall and temperature values using meteorological station data collected for 30 years across the regions. We found that climate change adaptation has a significant impact on both farm productivity and farm net revenues. We complement the analysis by providing an estimation of the determinants of adaptation. Extension services (both formal and farmer to farmer), as well as access to credit and information on future climate changes are key drivers of adaptation.

Keywords   Adaptation · Climate change · Farm level productivity · Instrumental variables · Rainfall · Ethiopia

1 Introduction

There is a growing consensus in the scientific literature that over the coming decades, higher temperature and changing precipitation levels caused by climate change will depress crop yields in many countries (Orindi et al. 2006; Stige et al. 2006). This is particularly crucial in

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low-income countries, where adaptive capacity is perceived to be low (IPCC 2007). Many African countries, which have economies largely based on weather-sensitive agricultural production, are particularly vulnerable to climate change (Mendelsohn 2000; IPCC 2007; Kurukulasuriya et al. 2006). This vulnerability has been demonstrated by the devastating effects of recent flooding and the various prolonged droughts of the twentieth century. Thus, for many poor countries that are highly vulnerable to the effects of climate change, understanding farmers' responses to climatic variation is crucial in designing appropriate coping strategies to climate change.

When evaluating the impacts of climate change on agriculture, two approaches have become the most widely used methods: the agronomic (or crop) model and the Ricardian (or hedonic) model. Agronomic models are biophysical representations of crop production simulating the relevant soil-plant-atmospheric components that determine plant growth and yield. They can be used to assess the impacts of climate change on agricultural productivity, as well as to investigate the potential effects of different adaptation options. However, this approach does not take into account economic considerations and human capital limitations both of which affect actual farm decisions. On the other hand, Ricardian models are based on the idea that the long-term productivity of land is reflected in its asset value. The impacts of different influences on land value or farm net revenues,[1] including climatic differences, are estimated using cross-sectional data. After estimating how climate conditions (i.e., changes in temperature or precipitation) affect land values or farm net revenues, it is possible to use climate scenarios to infer the impact of climate change on the value of farmland and, hence, its productivity. The approach assumes that, over the longer term, a new climate regime will induce geographic redistribution of agricultural activity and other behavioral changes that are reflected in how farmers have adapted to different climate conditions in different geographical areas in the past.

The Ricardian approach implicitly incorporates adaptive behavior in its analysis. Land values, for instance, at a particular point in time are assumed to include future climate changes and potential adaptation measures. Adaptation is, however, an endogenous decision governed by a host of factors,[2] some observable and some not., Parameter estimates provided via Ricardian cross-sectional analysis can thus be affected because of unobservable heterogeneity. Failure to account for both endogeneity and unobservable heterogeneity (e.g., differences in farmers' abilities) may lead to biased estimates and misleading conclusions (Deschenes and Greenstone 2007).

This study aims to contribute to the expanding literature on climate change in agriculture (Mendelsohn et al. 1994, 1996, 2001; Mendelsohn and Dinar 1999, 2003; Deressa 2006; Kurukulasuriya et al. 2006; Schlenker et al. 2006; Kurukulasuriya and Mendelsohn 2008a,b; Seo and Mendelsohn 2008a,b; Wang et al. 2008; Lobell et al. 2008) by examining the impact of key climatic variables on agriculture in a low-income country. We focus on both food productivity and farm revenues and their relationship with climatic variables. We account for endogeneity concerns and estimate this relationship via both OLS and IV estimators. Moreover, we undertake the analysis also at the plot level. This allows us to employ both

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[1] It should be noted that a key assumption of the Ricardian approach is that land markets are functioning properly. Land prices will, therefore, reflect the present discounted value of land rents into the infinite future (Deschenes and Greenstone 2007). Land markets, however, may not be properly operating in areas of Africa where land property rights are not perfectly assigned. For example, large areas of Ethiopia are plagued by ill-defined property rights and tenure insecurity, making the application of the Ricardian model less feasible. This can, however, be circumvented with the use of net revenues.

[2] There is also a growing literature that analyze adaptation decisions at regional level (e.g., Admassie et al. 2007) in developing countries.

pseudo-fixed effect and two-stage least-square estimators to control for unobserved heterogeneity and endogeneity. The implementation of these procedure should ensure robustness of our results and conclusions.

We have access to a unique data set with household specific climate information to understand the impact of climatic factors on climate change adaptation decisions, net revenues and yields. Lack of enough spatial variation on key climatic variables (precipitation and temperature) in cross-sectional data is one bottleneck to conducting a micro level study on climate change (Di Falco et al. 2011).[3] This is particularly true in developing countries, where one meteorological station is set to cover a wide geographic area. To address this problem, 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 for each household. To bring more insights into adaptation strategies that are crucial to coping with climatic variability and change, this study also investigates key factors that govern farmers' decisions to use climate change adaptations and the impact of this action on food production.

The rest of the paper is organized as follows. In Sect. 2, we provide a background to climate change and agricultural production in Ethiopia. Section 3 details the survey design and the data employed in the empirical analysis. Section 4 provides some descriptive statistics on climate change and adaptation strategies in the study site. The econometric estimation methodology, along with some considerations in the estimation procedure, is provided in Sect. 5. Section 6 presents the empirical findings, while Sect. 7 concludes the paper.

2 Climatic Change and Agricultural Production in Ethiopia

Ethiopia is one of the least developed countries in the world with a gross national income (GNI) of US$22.7 billion and a population of more than 80 million (World Bank 2009). Agriculture is the source of livelihood to an overwhelming majority of the Ethiopian population and is the basis of the national economy, where small-scale subsistence farming is predominant. This sector employs more than 80% of the labor force and accounts for 45% of the GDP and 85% of the export revenue (Ministry of Finance and Economic Development 2006). Ethiopian agriculture is heavily dependent on natural rainfall, with irrigation agriculture accounting for less than 1% of the country's total cultivated land. Thus, the amount and temporal distribution of rainfall and other climatic factors during the growing season are critical to crop yields and can induce food shortages and famine.

Ethiopia is a country with large heterogeneity in terms of its agro-ecology,[4] even within smaller administrative units. The agro-ecological zonation currently used for agricultural planning and development was developed by Hurni as part of the Soil Conservation Research

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[3] There is a very large literature on the impact of climate change on agriculture using either agronomic and Ricardian approach at regional level (e.g., Pearce et al. 1996; McCarthy et al. 2001; Parry et al. 2004; Deressa 2006; Stern 2007). Regional level studies can be useful in appreciating the magnitude of the problem and to design appropriate mitigation strategies at the national or regional levels, especially when agroecological and meteorological conditions do not change much spatially (e.g., Reilly et al. 1996; Rosenzweig and Parry 1994; Gregory et al. 2002; Amthor 2001; Fuhrer 2003; Giorgis et al. 2006). However, they are less relevant in terms of providing critical insights for effective adaptation strategies at the household level.

[4] Agro-ecological zonation can be defined as a spatial classification of the landscape into area units with "similar" agricultural and ecological characteristics such as (a) comparable agro-climatic conditions for annual cropping, perennial crops, or agro-forestry, (b) similar conditions for livestock raising, (c) comparable land resource conditions such as soil, water or vegetative parameters, or (d) similar land management conditions such as raggedness of agricultural land, slope steepness, or topography in general.

Project (SCRP) that was operational during 1987–1995 (Hurni 1998). Based on this classification, the entire country falls into six major agro-ecological zones. These are *Bereha* (desert, below 500 m a.s.l.), *Kolla* (lowlands, 500–1,500 m a.s.l.), *Weynadega* (midlands, 1,500–2,300 m a.s.l.) and *Dega* (highlands, 2,300–3,200 m a.s.l.), *Highdega* (3,200–3,700 m a.s.l.) and *Wurch* (above 3,700 m a.s.l.).[5] The surveyed districts fall into three of these (*Dega, Weynadega, Kolla*). *Kolla* is characterized by yellow sandy soils and is suitable only for acacia trees. Where moisture retention terraces are installed, however, it is suitable for the production of sorghum and ground nuts. *Weynadega* is characterized by light and red brown soils. The production environment is suitable for wheat, maize and *teff* (most popular cereal in the country). Maize and wheat, along with barley, are also widely grown in *Dega* and *Highdega*. The soils are typically brown and dark brown clay. The zones have two cropping seasons per year (long and short rainy seasons). Mean annual rainfall varies widely, ranging from about 1,200 mm over some pocket areas in *Kolla* to less than 250 mm. Mean annual temperature varies from about 12°C over the highlands in the *Dega* zone to about 27°C on the *Kolla* zone.

A recent mapping on vulnerability and poverty in Africa (Orindi et al. 2006; Stige et al. 2006) put Ethiopia as one of the countries most vulnerable to climate change with the least capacity to respond. Ethiopia has suffered from periodical extreme climate events, manifested in the form of frequent drought (1965, 1974, 1983, 1984, 1987, 1990, 1991, 1999, 2000, 2002, 2011) and occasional flooding (1997 and 2006). Rainfall variability and associated droughts have been major causes of food shortage and famine in Ethiopia. At the national scale, the link between drought and crop production is widely known. However, little evidence is available on how climate change affects farmers' adaptation strategies at the household level and the subsequent crop yield and revenues (notable exceptions are Seo and Mendelsohn 2008a,b and Di Falco et al. 2011). This is particularly important for designing effective adaptation strategies to cope with the potential impacts of climate change.

3 Description of the Study Sites and Survey Instruments

The study is based on a rural household survey conducted on 1,000 households located within the Nile Basin of Ethiopia, which covers more than a third of the country, including the major agricultural production areas. The sample districts (*weredas*[6]) were purposely selected to include different attributes of the basin, including the traditional typology of agro-ecological zones (i.e. *Dega, WeynaDega, Kola*, and *Bereha*), percentage of cultivated land, degree of irrigation activity, and vulnerability (proportion of population dependent on food aid). Peasant associations or *Kebeles* (administrative units smaller than districts) were also purposely selected to include households with the above attributes. One peasant association is selected from each of 20 districts. Once the peasant associations were chosen, 50 farmers were randomly selected from each peasant association, which gave a total of 1,000 interviewed households.

As in many parts of Ethiopia, the farming system in our survey sites is still very traditional, with plough and yolk (animal draught power) and labor as the major means of production during land preparation, planting, and post-harvest processing. Rain-fed agriculture is a common practice for many farm households, with only few (0.6%) using irrigation water to grow their crops.

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[5] More detail on Ethiopia's agro-ecological classification can be obtained at Hurni (1998).

[6] *Wereda* is the second lowest administrative unit (next to *kebele*) in Ethiopia.

Production input and output data were collected for two cropping seasons—*Mehere* (the long rainy season) and *Belg* (the short rainy season)—at plot level. Very few plots exhibit a biannual cropping pattern (growing during both the *Mehere* and the *Belg* seasons). We estimated a production function only for the *Mehere* cropping season.

Detailed data on the cost of the production were collected at different production stages at plot level: land preparation, planting, weeding, harvesting, and post-harvest processing. Labor inputs were disaggregated as adult male, adult female, and children. This approach of collecting data (both inputs and outputs) at different stages of production and at different levels of disaggregation reduces cognitive burden on the side of the respondents, while increasing the likelihood of retrieving better retrospective data. In our production function, the three forms of labor were aggregated as one labor input using adult equivalents.[7]

Monthly rainfall and temperature data were collected from all the meteorological stations in the entire country for 30 years. We then used the Thin Plate Spline method. of spatial interpolation to impute the household-specific rainfall and temperature values using each household's latitude, longitude, and elevation information. For a description of the Thin Plate Spline method please see Wahba (1990), and Hong et al. (2005). The spatial interpolation was limited by the small number of gauge stations from which temperature and rainfall data were available and the incomplete information for latitude, longitude, and elevation of each household. It should be noted that any spatial interpolation is subject to uncertainty associated with the choice of interpolation method, measurement errors, and large variability on altitude, slope and other spatial factors. Given the limitations of spatial interpolation of rainfall data, the best method to improve the quality of spatial rainfall estimation is to increase the density of the monitoring network, and test the validity of the interpolation by conducting counter interpolation (Hutchinson 1998). Like many other developing countries, we have few meteorological stations around each one of our study sites. Thus, in order to minimize the uncertainties, we used more data points (30 years monthly rainfall data obtained from each rain gauge station) to interpolate the rainfall data. This should help us to minimize the potential uncertainty and noise from the interpolation exercise. In this paper, we used the expertise of hydrologist and GIS personnel at the International Food Policy Research Institute (IFPRI) to conduct the interpolation. Similar procedures were adopted in the hydrology literature by Hutchinson (1998), Mckenney et al. (2000), and many other similar studies.

Finally, although a total of 48 annual crops were grown in the basin, the five major annual crops (teff, maize, wheat, barley, and beans) cover 65% of the plots. Our estimation is limited to these crops. The scale of analysis is at both the farm and plot level. Descriptive statistics are reported in Table 1.

4 Climate Change and Adaptation in the Study Sites

One of the survey instruments was designed to capture farmers' perceptions and understanding of climate change, as well as their adaptation approaches.[8] Questions asked included whether the farmers had noticed changes in mean temperature and rainfall over the past two decades and the perceived reasons for these observed changes. About 68% perceived mean temperature as increasing over the past 20 years; 4%, as decreasing; and 28%, as remaining

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[7] We employed the OECD/EU standard conversion factor in the literature in developing countries, where adult female and child labor are converted into the adult male labor equivalent with the conversion factors 0.8 and 0.3, respectively.

[8] We separately asked questions about experience with and coping mechanisms related to climate-related shocks (droughts, floods, hailstorms, and fires). These analyses are not reported here.

Table 1 Basic descriptive statistics of sampled farm households

Variables	Mean	SD	Minimum	Maximum
Household/head characteristics				
Gender of household head (1 = male)	0.92	0.26	0	1
Age of household head (years)	45	14	16	92
Marital status of head (1 = married)	0.90	0.29	0	1
Literate household head (1 = yes)	0.49	0.50	0	1
Household size	6.6	2.2	1	15
Access to formal and informal institutional support				
Access to formal (crop) extension (1 = yes)	0.60	0.49	0	1
Farmer-to-farmer extension (1 = yes)	0.51	0.50	0	1
Access to formal credit (1 = yes)	0.26	0.44	0	1
Number of relatives in a village	17	43	0	170
Climatic factors and adaptations				
Belg (short rain season) rainfall (mm) average 1950–2000	312	132	84	641
Mehere (long rain season) rainfall (mm) average 1950–2000	1,120	340	301	1,777
Average temperature (°C) average 1970–2000	17.7	2.0	13	24
Information received on climate change through extension (1 = yes)	0.43	0.49	0	1
Adaptation to climate change (1 = yes)	0.63	0.48	0	1
Agro-ecology				
Lowlands (*Kolla*)	0.21	0.41	0	1
Midlands (*WeynaDega*)	0.48	0.50	0	1
Highlands (*Dega*)	0.31	0.46	0	1
Production inputs and outputs				
Net revenues (in Ethiopian Birr)	3,837	3,255	0	29,628
Output per hectare (kg)	1,026	1,194	0	2,000
Seed use per hectare (kg)	114	148	10	260
Fertilizer use per hectare (kg)	60	175	0	410
Manure use per hectare (kg)	206	888	0	1,740
Labor use per hectare (adult days)	103	172	2.18	2,128
Soil fertility (1 = highly fertile, 2 = moderately fertile, 3 = infertile)	1.8	0.53	1	3

the same. Similarly, 18% perceived mean annual rainfall as increasing over the past 20 years; 62% as declining; and 20% as remaining the same. Figure 1 depicts farmers' perceptions of climate change in our study sites. Overall, increased temperature and declining precipitation are the predominant perceptions in our study sites. These perceptions that become part of personal experience are very important in explaining adaptation (Smithers and Smit 1997; Roncoli et al. 2002; Vogel and O'Brien 2006).

In response to these long-term perceived changes, farm households in our study sites have undertaken a number of adaptation measures, including changing crop varieties, adoption of soil and water conservation measures, water harvesting, tree planting, and changing planting and harvesting periods. These adaptation measures are mainly yield related and account for more than 95% of the measures. The remaining adaptation measures (amounting to less than
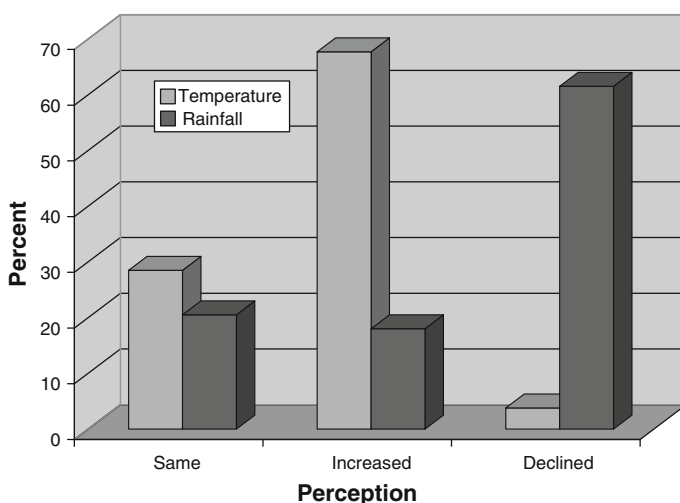
Fig. 1 Households' perceptions on climate change over the past 20 years

5%) were non-yield related and include migration and a shift in farming practices from crop production to livestock herding or other sectors.

About 58% did not undertake adaptation measures in response to long-term shifts in temperature and 42% did not undertake adaptation measures in response to long-term shifts in precipitation. More than 90% of the respondents who took no adaptation measures indicated lack of information and shortages of labor, land, and money as major reasons for not doing so. In fact, lack of information was cited as the predominant reason by 40–50% of the households. It should be noted that the lack of information may be interpreted as lack of information on how to deal with the perceived change in climate. These results are summarized in Tables 2 and 3.

Table 2 Adjustments made to long-term shifts in climate (in percentage)

	Temperature	Rainfall
Nothing	56.8	42.0
Implement soil conservation schemes	2.9	31.1
Changed crop variety	20.0	11.1
Planted trees	13.3	2.9
Harvested water	0.3	4.1
Sought off-farm activities	0.9	0.8
Planted late	0.4	0.4
Planted early	2.0	4.1
Migrated to urban area	0.2	1.1
Used irrigation	1.4	2.3
Sold livestock	1.4	0.1
Changed farming type (from crop to livestock)	0.2	0.3
Adopted new technologies	0.2	0.4

Table 3 Constraints to farm-level adaptations (in percentage)

Reason for not doing the following	Lack of information	Lack of money/credit	Labor shortage	Land shortage	Water shortage	Don't see the need	Other reasons
Changing crop varieties	52	36	3	4	0.2	1	3.8
Water harvesting	41	27	18	3	1	2	8
Soil conservation	47	11	26	2	1	13	0
Planting trees	42	9	17	18	2	9	3
Irrigating	24	27	16	10	15	2	6

5 Empirical Approach

We framed our analysis using the standard theory of technology adoption, wherein the problem facing a representative risk-averse farm household is to choose a mix of climate change adaptation strategies that will maximize the expected utility from final wealth at the end of the production period, given the production function and land, labor, and other resource constraints, as well as climate. Assuming that the utility function is state independent, solving this problem would give an optimal mix of adaptation measures undertaken by the representative farm household, as given by

$$A_h = A\left(x_h^H, x_h^i, x_h^c, x_h^a; \beta\right) + \varepsilon_h \tag{1}$$

where A is the adaptation strategy of household h; x_h^H is a vector of household characteristics (such as gender, age, marital status of the "head" of the household, and household size), x_h^i is a vector to represent access to formal and informal institutions (such as access to formal extension, farmer-to-farmer extension, access to formal credit, and number of relatives in the village as proxy for social capital), x_h^c is a vector to capture climatic variables (such as *Belg* rainfall, *Mehere* rainfall, average temperature) and access to climatic information extension, and x_h^a is the agro-ecology of the farm household. β is the vector of parameters; and ε_h is the household-specific random error term. All the independent variables were identified based on economic literature predictions and earlier empirical studies reported earlier in this paper. Households will choose adaptation strategy 1 over adaptation strategy 2 if and only if the expected utility from adaptation strategy 1 is greater than that from adaptation strategy 2, that is:

$$E\left[U(A_1)\right] > E\left[U(A_2)\right].$$

The choice of adaptation strategy is conditioned on a host of climatic, agro-ecological and socio-economic factors. This study focuses on the adaptation definition per se and we therefore employ a dummy variable to measure whether farm households had adopted *any* measure in *any* of their plots in response to perceived climate changes. These adaptation measures are elicited at household level, not plot level. Our results should therefore be interpreted under this caveat. A probit regression was used to estimate determinants of adaptation as specified by Eq. (1). Another objective of this study is to investigate whether climate change and adaptation have any impact on food production or farm net revenue. This can be done by including the dummy variable for adaptation in a standard household production function

$$y_h = f\left(x_h^c, A_h, x_h^s, x_h^a, \gamma\right) + \xi_h \qquad (2)$$

where x_h^c, A_h are vectors of climatic variables (*Belg* and *Mehere* rainfall and temperature including square terms), and climatic adaptation measures, respectively. x_h^s captures standard production inputs (such as seeds, fertilizers, manure and labor inputs), and x_h^a captures agro-ecology of the farm household; γ is a vector of parameters; and ξ_h is a household-specific random error term. We first estimate Eq. (2) at the farm household level. We also implemented the analysis in a Ricardian setting and use net revenues as the dependent variable. This can be particularly useful in this setting where the yields of different crops are aggregated. The Ricardian approach use monetary values and therefore makes aggregation much more straightforward.

As mentioned in the previous section we have access to plot level production information. In Ethiopia, intercropping within a plot is not a common practice. Each plot is devoted to a specific (mostly cereal) crop. We exploited the availability of both farm and plot information and estimated Eq. (2) with and without the pseudo-fixed-effect model (Mundlak 1978; Wooldridge 2002). Controlling for unobservables seems appropriate in this situation. For instance, there may be correlation between plot invariant characteristics (i.e., farmers' skills) and adaptation. In this situation the use of the pseudo fixed effects specification enables consistent parameter estimates by controlling for unobserved heterogeneity that might be correlated with observed explanatory variables. In order to do so, the right side of our pseudo-fixed-effect regression equation includes the mean value of the time (plot)-varying explanatory variables (Mundlak 1978). This approach relies on the assumption that unobserved effects are linearly correlated with explanatory variables, as specified by

$$\psi_h = \overline{x}\alpha + \eta_h, \eta_h \sim \text{iid}\left(0, \sigma_\eta^2\right) \qquad (3)$$

where $\overline{x}$ is the mean of the time (plot)-varying explanatory variables (such as average seed, fertilizer, manure and labor uses, and average soil fertility) within each household (cluster mean), α is the corresponding vector coefficient, and η is a random error unrelated to $\overline{x}'$s. The vector α will be equal to 0 if the observed explanatory variables are uncorrelated with the random effects. We conducted an F test against the null hypothesis that the vector α are jointly equal to zero and the test results rejected the null hypothesis and justified the relevance of fixed effects (Wooldridge 2002).[9]

To further address the issue of possible endogeneity bias, we considered the situation in which the correlation between the error term and climate adaptation would not happen via the individual fixed effect.[10] In this situation, only controlling for the plot–invariant unobservable characteristics may not be enough. The estimated coefficients could still be inconsistent. We therefore use some of the explanatory variables (e.g., access to formal extension, farmer-to-farmer extension and number of relatives in the village) in Eq. (1) as instruments and implemented a two stages least squares estimator. This estimator is consistent in the situation where the (presumably) endogenous variable is discrete (Angrist and Krueger 2001). The appropriate implementation of the estimator requires that the set of explanatory variables used as instruments should not be correlated with the error term in Eq. (2) but instead be correlated with the endogenous variables. To scrutinize our choice of instruments, we test for their relevance by using an F test of the joint significance of the excluded instruments. The

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[9] One may argue for the use of a standard fixed-effect model. It should be noted, however, that the latter relies on data transformation which removes the unobserved individual effect as well as variables that are constant across the plots. In our case, we have a mix between variables that are plot invariant (i.e. climate) and variables that are plot variant. It would not be feasible to estimate the parameters of the plot invariant variables.

[10] Endogeneity may also be an issue for other control variables (i.e. inputs)

F test of excluded instruments is equal to 16.28 for the farm level analysis and 49.96 for the plot level analysis. We can thus reject the null hypothesis, indicating that the instruments are relevant for both level of aggregation. We also tested the over-identification restrictions using a Sargan/Hansen test of over-identifying restrictions. We found an over-identified equation in which the number of instruments exceeded the number of covariates. Overall, we fail to reject the null hypothesis that the excluded instruments are valid. The instruments are uncorrelated with the error term and correctly excluded from the estimated equation. The full testing procedure is reported at the bottom of the Tables 5 and 6. To document the bias, we present also the results from the OLS estimator both with and without pseudo fixed effects.

6 Results and Discussion

Tables 4, 5, and 6 report the estimates of the empirical analysis. Table 4 presents the probit results of the adaptation regression. The decision to employ adaptation measures is assumed to be a function of climatic factors (*Belg* and *Mehere* rainfall levels, temperature level, information about climate change (and potential adaptation measures), household characteristics (i.e., gender, age, marital status, literacy, and household size), formal and informal institutional support (formal extension, farmer-to-farmer extension, access to credit, social capital) and the farm household's agro-ecological setting.

We gradually insert these covariates to document how the estimated coefficients of the climatic variables are affected. Results are broadly consistent. The estimates for climatic variables are statistically significant in all the specifications and we find strong significance for non-linear terms. The statistical significance of the climatic variable on the probability of adaptation can provide some evidence that the adaptation strategies undertaken by farmers are indeed correlated with climate. It could in fact be argued that some of these strategies (i.e. changing crops) are part of standard farming practices rather than climate per se. The evidence can offer some reinsurance that climate is a key driver behind the adaptation analyzed in this paper. Among the socioeconomic characteristics, only the household size is found to be positive and statistically significant. Access to formal and informal institutional support seems to play a very important role. Extension service (both farmer-to-farmer and from government) is positively correlated with the probability of adaptation. Information about climate change and adaptation measures also seems to govern a household's adaptation decisions. These results are consistent with a similar study by Deressa et al. (2008)[11], which used a multinomial logit model to analyze adaptation behavior in the Nile Basin. Among the inputs only fertilizer is statistically significant. The estimated coefficient is negative. It is therefore negatively correlated with the probability of adapting.

Table 5 reports the estimated results for both the production function and Ricardian model. The first three columns provide the results for the production function. We explored alternative functional forms and found the quadratic specification to be more robust. Column (1) reports the OLS results. Column (2) and (3) report the results of the IV estimator. Likewise, column (4) to (6) report the results for the Ricardian analysis.

It may be argued that pooling different crops can induce some bias. There maybe some underlying differences in their production functions for instance. To control for this possible source of heterogeneity we included some dummies to capture the specificity of the different crops. These results are reported in the columns (3) and (6).

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[11] This study is using the same dataset as Deressa et al. (2008).

Table 4 The determinants of on climate adaptation: probit estimates

	(1)	(2)	(3)	(4)
Climatic factors				
Mehere rainfall	−0.0105***	−0.0112***	−0.00575**	−0.00501**
	(0.00224)	(0.00230)	(0.00236)	(0.00253)
Mehere rainfall^2	0.00000647***	0.00000679***	0.00000335**	0.00000282*
	(0.00000127)	(0.00000133)	(0.00000140)	(0.00000147)
Belg rainfall	−0.0142***	−0.0127***	−0.00839***	−0.00590**
	(0.00191)	(0.00217)	(0.00253)	(0.00282)
Belg rainfall^2	0.0000133***	0.0000108***	0.00000573	0.00000109
	(0.00000279)	(0.00000316)	(0.00000372)	(0.00000430)
Average temperature	1.370***	1.435***	1.284***	1.224***
	(0.269)	(0.301)	(0.349)	(0.360)
Average temperature^2	−0.0353***	−0.0369***	−0.0336***	−0.0324***
Socio economic characteristics				
	(0.00648)	(0.00721)	(0.00837)	(0.00862)
Education		0.0135	−0.00289	−0.00395
		(0.0195)	(0.0225)	(0.0220)
HH size		0.0921***	0.0770***	0.0742***
		(0.0254)	(0.0270)	(0.0272)
Marital status		−0.108*	0.00986	0.0747
		(0.0616)	(0.0637)	(0.0777)
Age		−0.00311	−0.00387	−0.00416
		(0.00446)	(0.00459)	(0.00467)
Gender				−0.383
				(0.267)
Access to formal and informal institutional support				
Formal extension			0.432***	0.431***
			(0.150)	(0.152)
Farmer to farmer extension			0.435***	0.406**
			(0.154)	(0.161)
Access to credit			0.179	0.187
			(0.137)	(0.135)
Information on climate change			0.468***	0.475***
			(0.146)	(0.148)
Number of relatives in the village			0.00448	0.00382
			(0.00381)	(0.00379)
Inputs use and soil characteristics				
Soil fertility				0.0653
				(0.119)
Labour				0.00108
				(0.000900)

Table 4 continued

	(1)	(2)	(3)	(4)
Fertilizer				−0.000974*
				(0.000538)
Manure				0.000139
				(0.000131)
Seeds				−0.000437
				(0.000840)
Agro-ecology				
Midlands (*WeynaDega*)				0.0436
				(0.230)
Highlands (*Dega*)				0.303
				(0.184)
Constant	−6.390*	−7.080*	−5.994	−5.702
	(3.375)	(3.859)	(4.328)	(4.574)
N	940	878	828	828

Robust SE in parentheses $*p < 0.10$, $** p < 0.05$, $*** p < 0.01$

Both the production function and Ricardian estimates provide consistent results. Results show that the estimated coefficient for adaptation is positive and statistically significant. Farmers who adopt climate change adaptation strategies have higher food production and net revenues than those who do not. If households undertake adaptation measures they will be able to produce more food and obtain higher revenues in the face of climate change. This result is also consistent with the argument in the literature that climate change adaptation partially offsets the impact of climate change on food production, and exclusion of climate change adaptation in the analysis would overstate the impact of climate change on agricultural production (Dinar et al. 2008).

Most of the IV estimates of both the production and the Ricardian models highlight that rainfall can be significant in explaining variations of in yields and net revenues across farm households. We also find some evidence of non linearity. Results change qualitatively. To illustrate, consider the computation of the marginal effects (using the plot analysis and estimated at the sample means) for rainfall in the two different seasons. An increase of 100 mm of rainfall during the long rainy season will decrease the yields by 106 kg. The same increase during the short rainy season would instead have a positive impact on yields. These would increase by 111 kg. Too much or too little rain of both the *Belg* and *Mehere* rainfall seems to affect food production in our study sites. Adverse impacts of too much rain is consistent with other studies (You and Ringler 2010).

Third, all the conventional inputs exhibit signs consistent with predictions of economic theory, and all are statistically significant. As expected, more use of seeds, fertilizers, manure, and labor tend to increase food production. There is also a significant difference across agroecologies once the standard production inputs, climatic variables, and climate adaptation variables were controlled for. More food per hectare was being produced in highlands (*Dega*), followed by lowlands (*Kolla*), and finally the midlands (*WeynaDega*).

Table 6 reports the coefficient estimates of the pseudo fixed effect model. Again the results are very similar. Adaptation is positively correlated to both production and net revenues. The results provided in Table 5 are thus consistent after controlling for plot invariant character-

Table 5 The role of adaptation in food production and Ricardian models—OLS and IV estimates

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Adaptation and climatic factors						
Climate adaptation	117.7**	502.6**	507.0*	453.0**	1893.8**	1708.1*
	(48.12)	(256.0)	(260.7)	(221.9)	(929.6)	(947.7)
Mehere rainfall	−0.231	0.987	1.039	8.094***	13.02***	9.665**
	(0.797)	(1.060)	(1.108)	(2.993)	(3.777)	(4.066)
Mehere rainfall^2	0.0000193	−0.000750	−0.000812	−0.00451***	−0.00757***	−0.00598**
	(0.000441)	(0.000639)	(0.000650)	(0.00168)	(0.00230)	(0.00242)
Belg rainfall	1.372	2.488**	2.387**	7.934**	12.27***	15.80****
	(0.977)	(1.160)	(1.174)	(3.997)	(4.654)	(4.698)
Belg rainfall^2	−0.00189	−0.00256*	−0.00235	−0.0112*	−0.0141**	−0.0204***
	(0.00141)	(0.00148)	(0.00154)	(0.00582)	(0.00614)	(0.00625)
Average temperature	30.56***	17.53	15.53	57.27	10.57	55.42
	(10.24)	(15.65)	(16.05)	(44.79)	(62.72)	(64.46)
Average temperature^2	−0.0543***	−0.0268	−0.0228	−0.0840	0.0145	−0.0671
	(0.0210)	(0.0324)	(0.0331)	(0.0914)	(0.129)	(0.132)
Production inputs						
Soil fertility	−91.98**	−91.55*	−89.51*	−279.3	−305.8	−328.1
	(45.41)	(47.73)	(47.71)	(193.0)	(204.5)	(201.0)

Table 5 continued

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Labour	3.036***	3.131***	2.998***	10.63***	10.95***	12.42***
	(0.616)	(0.635)	(0.639)	(2.490)	(2.550)	(2.565)
Fertilizer	0.794**	0.769**	0.712*	4.277***	4.101***	3.880***
	(0.351)	(0.364)	(0.380)	(1.475)	(1.530)	(1.527)
Manure	0.140	0.110	0.110	−0.0712	−0.201	−0.0737
	(0.115)	(0.120)	(0.115)	(0.448)	(0.459)	(0.445)
Seeds	2.167***	2.086***	2.262***	9.223***	8.909***	6.839**
	(0.571)	(0.609)	(0.697)	(2.962)	(3.075)	(3.339)
Labour^2	−0.00217**	−0.00233**	−0.00227**	−0.00754*	−0.00814*	−0.00899**
	(0.000940)	(0.000964)	(0.000953)	(0.00424)	(0.00432)	(0.00415)
Fertilizer^2	−0.000259**	−0.000231**	−0.000214*	−0.00159***	−0.00145***	−0.00132***
	(0.000107)	(0.000110)	(0.000116)	(0.000453)	(0.000481)	(0.000476)
Manure^2	−0.0000238	−0.0000256	−0.0000254	0.00000236	−0.00000380	−0.0000171
	(0.0000160)	(0.0000167)	(0.0000162)	(0.0000651)	(0.0000683)	(0.0000687)
Seeds^2	0.000987	0.00110	0.00101	0.00380	0.00427	0.00514
	(0.000720)	(0.000711)	(0.000724)	(0.00395)	(0.00393)	(0.00381)
Agro-ecology						
Midlands (*WeynaDega*)	−286.9***	−287.3***	−287.2***	−1947.1***	−1987.0***	−1751.4***
	(99.45)	(107.4)	(107.3)	(361.5)	(389.3)	(377.5)
Highlands (*Dega*)	−561.0***	−611.4***	−597.1***	−2310.2***	−2525.2***	−2371.3***
	(76.48)	(83.55)	(88.72)	(298.0)	(329.7)	(337.7)

Table 5 continued

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummies for different crops						
Dummy for wheat			43.90			300.1
			(54.22)			(200.1)
Dummy for teff			30.44			659.1***
			(56.15)			(212.9)
Dummy for maize			68.17			−305.1
			(83.86)			(279.7)
Dummy for beans			−40.01			509.1**
			(61.39)			(257.5)
Constant	−3266.6**	−2602.5	−2420.0	−9650.6	−7509.0	−12700.6*
	(1389.1)	(1703.3)	(1756.2)	(5873.0)	(6987.9)	(7036.4)
N	939	899	899	939	899	899
Adj. R^2	0.339	0.304	0.302	0.309	0.280	0.298

Testing for model (3): Partial R-squared of excluded instruments: 0.0623. Test of excluded instruments: $F(3, 874) = 16.28$ Prob $> F = 0$. Hansen J statistic (overidentification test of all instruments): 0.412 Chi-sq(2) P value = 0.81. Durbin–Wu–Hausman chi-sq test: 3.31 Chi-sq(1) P value = 0.06884. Testing for model (6): Partial R-squared of excluded instruments: 0.0623. Test of excluded instruments: $F(3, 874) = 16.28$ Prob $> F = 0$. Hansen J statistic (overidentification test of all instruments 1.456 Chi-sq(2) P value = 0.48. Durbin–Wu–Hausman chi-sq test: 2.44 Chi-sq(1) P value = 0.12. Robust SE in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Food production and Ricardian model: plot level analysis with pseudo-fixed-effect

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Adaptation and climatic factors						
Climate adaptation	187.6***	399.4*	446.9**	785.6***	1750.7**	1656.7**
	(42.88)	(213.1)	(210.6)	(188.3)	(868.1)	(827.0)
Mehere rainfall	0.359	1.409	1.822*	8.860***	13.44***	7.857**
	(0.702)	(1.040)	(1.049)	(2.683)	(3.972)	(3.826)
Mehere rainfall^2	−0.000441	−0.00108*	−0.00129**	−0.00568***	−0.00845***	−0.00553**
	(0.000390)	(0.000612)	(0.000614)	(0.00152)	(0.00238)	(0.00228)
Belg rainfall	2.663***	3.423***	3.085***	10.70***	13.88***	12.44***
	(0.769)	(0.914)	(0.922)	(3.223)	(3.795)	(3.561)
Belg rainfall^2	−0.00320***	−0.00373***	−0.00312***	−0.0134***	−0.0154***	−0.0129***
	(0.00108)	(0.00113)	(0.00115)	(0.00460)	(0.00482)	(0.00457)
Average temperature	42.74***	38.82***	31.09**	57.50	34.76	83.59
	(8.851)	(12.37)	(12.27)	(43.36)	(58.65)	(55.12)
Average temperature^2	−0.0784***	−0.0697***	−0.0547**	−0.0817	−0.0317	−0.128
	(0.0179)	(0.0254)	(0.0252)	(0.0894)	(0.122)	(0.115)
Production inputs						
Soil fertility	−103.7***	−102.1***	−93.25***	−264.4**	−270.7**	−289.3**
	(27.62)	(28.49)	(28.51)	(122.9)	(127.7)	(119.1)

Table 6 continued

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Labour	3.324***	3.365***	3.123***	11.53***	11.58***	9.886***
	(0.439)	(0.445)	(0.438)	(2.619)	(2.650)	(2.641)
Fertilizer	0.769**	0.717**	0.806**	3.289***	3.172**	3.629***
	(0.299)	(0.308)	(0.329)	(1.236)	(1.273)	(1.291)
Manure	0.222***	0.211**	0.165*	0.274	0.247	0.491
	(0.0837)	(0.0857)	(0.0847)	(0.403)	(0.411)	(0.387)
Seeds	1.955***	1.992***	2.210***	4.640**	4.469**	6.732***
	(0.400)	(0.426)	(0.475)	(2.069)	(2.149)	(2.403)
Labour^2	−0.00135***	−0.00140***	−0.00129***	−0.00277	−0.00287	−0.00192
	(0.000488)	(0.000484)	(0.000490)	(0.00364)	(0.00364)	(0.00361)
Fertilizer^2	−0.000131	−0.000116	−0.000143	−0.000730*	−0.000688	−0.000791*
	(0.000128)	(0.000129)	(0.000131)	(0.000441)	(0.000444)	(0.000458)
Manure^2	−0.0000245**	−0.0000236**	−0.0000192*	−0.0000231	−0.0000216	−0.0000511
	(0.0000115)	(0.0000117)	(0.0000115)	(0.0000704)	(0.0000720)	(0.0000657)
Seeds^2	0.000706**	0.000704**	0.000613**	0.00506**	0.00517**	0.00409*
	(0.000294)	(0.000299)	(0.000310)	(0.00246)	(0.00247)	(0.00244)
Agro-ecology						
Midlands (*WeynaDega*)	−326.2***	−348.3***	−420.5***	−2134.8***	−2260.7***	−1890.5***
	(88.21)	(89.60)	(89.46)	(299.4)	(311.2)	(299.5)
Highlands (*Dega*)	−600.8***	−648.5***	−667.2***	−2471.0***	−2698.1***	−2611.2***
	(65.92)	(74.90)	(74.70)	(233.7)	(272.8)	(262.7)

Table 6 continued

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummies for different crops						
Dummy for wheat			−75.47			2779.0***
			(74.26)			(224.0)
Dummy for teff			−173.0**			2909.7***
			(78.88)			(300.5)
Dummy for maize			165.2*			2134.7***
			(88.48)			(319.1)
Dummy for beans			−149.3*			4285.6***
			(89.78)			(406.7)
Mean value of plot varying variables						
Average labour use	−1.606***	−1.606***	−1.530***	−8.696***	−8.696***	−7.227***
	(0.509)	(0.509)	(0.506)	(2.440)	(2.440)	(2.381)
Average fertilizer use	−0.388*	−0.388*	−0.429**	−0.909	−0.909	−0.817
	(0.210)	(0.210)	(0.215)	(0.802)	(0.802)	(0.772)
Average manure use	−0.0850	−0.0850	−0.0720	−0.138	−0.138	−0.222
	(0.0597)	(0.0597)	(0.0599)	(0.302)	(0.302)	(0.285)

Table 6 continued

Dependent variable	OLS	IV	IV	OLS	IV	IV
	Quantity per hectare			Net revenues		
	(1)	(2)	(3)	(4)	(5)	(6)
Average seeds use	1.154***	1.154***	1.152***	6.387***	6.387***	4.547**
	(0.442)	(0.442)	(0.430)	(1.953)	(1.953)	(1.771)
Constant	−5132.0***	−5351.9***	−4495.9***	−9809.3*	−10057.6	−15985.4***
	(1245.5)	(1393.4)	(1385.0)	(5708.4)	(6419.4)	(6021.0)
N	2777	2656	2656	2777	2656	2656
Adj. R^2	0.312	0.308	0.313	0.303	0.298	0.359

Testing for model (3): Partial R-squared of excluded instruments: 0.06. Test of excluded instruments: $F(3, 2,631) = 49.96$ Prob $> F = 0$. Hansen J statistic (overidentification test of all instruments 2.186 Chi-sq(2) P value = 0.33. Durbin–Wu–Hausman chi-sq test: 1.69 Chi-sq(1) P value = 0.19. Testing for model (6): Partial R-squared of excluded instruments: 0.06. Test of excluded instruments: $F(3, 2,631) = 49.96$ Prob $> F = 0$. Hansen J statistic (overidentification test of all instruments): 2.186 Chi-sq(2) P value = 0.33. Durbin–Wu–Hausman chi-sq test 1.5 Chi-sq(1) P value = 0.21. Robust SE in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

istics. It should be noted that some of the parameter estimates of the means of plot-varying variables—α in Eq. (3)—are significant. This indicates that the robustness check through pseudo-fixed effects is appropriate.

7 Concluding Remarks

This paper presents a micro-level study on the impact of climate change and climate adaptation on food production in the Nile basin of Ethiopia. To this end we use a rich data set from a plot level survey of 1,000 farms. Farm production and adaptation data were complemented with household specific weather information. Weather data were obtained by the interpolation of meteorological data. We found that household characteristics, age and literacy of the household head are important drivers of adaptation. Both formal extension and farmer-to-farmer extension, as well as extension regarding climatic adaptation information were positively and significantly correlated to the adoption decision. The same result was found for access to formal credit and number of relatives in the village. Not surprisingly, the adoption decision was also affected by climatic factors such as rainfall and temperature, as well as the agro-ecological setting.

To empirically test for the role of adaptation on productivity we use three different estimating strategies: OLS, a pseudo panel data approach and an IV estimator. We adopt both a productivity setting and a Ricardian approach. Results are consistent and indicate that climate change adaptation has a positive and significant impact on food production in one of the most vulnerable agricultural regions in the world. The impact of adaptation is not trivial. We estimated that the household that with climate change adaptation have an extra 10% in terms of net revenues. Both approaches were extended to take into consideration the significant impact of climate factors, standard production inputs and agro-ecological setting. Consistently with existing literature we find that climatic variables have non linear effects.

A number of policy conclusions can be drawn from this study. First of all, it is important to analyze the impacts of climate change on agriculture and simultaneously understand the drivers behind farmers adaptation. Secondly, the current attention given to climate adaptation has the potential to go hand-in-hand with the long-term policy priority in increasing production and reducing vulnerability among poor farmers in developing countries. The great potential for effective policy intervention is particularly evident from the factors that affect climate change adaptation. Many of the significant factors can be addressed as part of rural development programs, such as literacy, formal extension, access to formal credit and provision of information about climate variables and adaptation options. Many of these activities are also traditional components of rural development programs. This stresses the importance of not treating climate change adaptation interventions separately from other rural development and poverty alleviation interventions, but rather complement them with specific activities to raise the awareness of farmers regarding climate change and increase their capacity to adapt to the challenges that climate change implies.

Future research is needed to better understand the microeconomics of the adaptation process. The availability of micro panel data can provide more robust evidence on both the role of adaptation and its implications for productivity. Future research efforts should also be devoted to the distinction of the different adaptation strategies and the identification of the most successful ones for both the medium and longer term. Future research on plot level adaptation measures would help to gain more insights in terms of plot level heterogeneity of climate change adaptation decisions. Given the information we have in our survey, the household level dummy variable was a preferred and a plausible alternative for measuring

whether a particular household had adopted an adaptation strategy to avert or minimize the adverse effects of perceived climate change.

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