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WPS4603

Policy Research Working Paper 4603

A Structural Ricardian Analysis of Climate Change Impacts and Adaptations in African Agriculture

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The World Bank
Development Research Group
Sustainable Rural and Urban Development Team
April 2008

Policy Research Working Paper 4603

Abstract

This paper develops a Structural Ricardian model to measure climate change impacts that explicitly models the choice of farm type in African agriculture. This two stage model first estimates the type of farm chosen and then the conditional incomes of each farm type after removing selection biases. The results indicate that increases in temperature encourage farmers to adopt mixed farming and avoid specialized farms such as crop-only or livestock-only farms. Increases in precipitation encourage farmers to shift from irrigated to rainfed crops. As temperatures increase, farm incomes from crop-only farms or livestock-only farms fall whereas incomes from mixed farms increase. With precipitation increases, farm incomes from irrigated farms fall whereas incomes from rainfed farms increase. Naturally, the Structural Ricardian model predicts much smaller impacts than a model that holds farm type fixed. With a hot dry climate scenario, the Structural Ricardian model predicts that farm income will fall 50 percent but the fixed farm type model predicts farm incomes will fall 75 percent.

This paper—a product of the Sustainable Rural and Urban Development Team, Development Research Group—is part of a larger effort in the department to mainstream research on climate change. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at Niggol.seo@yale.edu and Robert.mendelsohn@yale.edu.

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Produced by the Research Support Team

A STRUCTURAL RICARDIAN ANALYSIS OF CLIMATE CHANGE IMPACTS AND ADAPTATIONS IN AFRICAN AGRICULTURE[1]

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[1] This paper is one of the product of a study "Measuring the Impact of and Adaptation to Climate Change Using Agroecological Zones in Africa" funded by the KCP Trust Fund and conducted in DECRG at the World Bank. We benefited from comments on an earlier draft by David Zilberman.
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1. Introduction

This paper develops a Structural Ricardian model to measure climate change impacts on agriculture that explicitly captures adaptation decisions by farmers (Seo and Mendelsohn 2007). Many recent studies of climate change impacts on agriculture have failed to fully include adaptations (Rosenzweig and Parry 1994, Schlenker et al. 2005, Deschenes and Greenstone 2007). By failing to properly capture adaptations, these studies overstate the actual damages that will occur with climate change. However, one of the most important insights of microeconomics is that economic agents will adapt to changing conditions. The Structural Ricardian model explicitly models the adaptive behaviors of farmers in measuring the impacts of climate change on agriculture.

The traditional Ricardian model (Mendelsohn, Nordhaus and Shaw 1994) captures adaptation in its measurement of impacts, but the adaptations are a black box, never explicitly measured or identified. In contrast, the Structural Ricardian model explicitly identifies adaptation measures and quantifies their influence on impacts. Several versions of the Structural Ricardian model have been explored that examine irrigation, crop species choice, and livestock species choice (Kurukulasuriya and Mendelsohn 2007; 2008; Seo and Mendelsohn 2007). The approach was also applied to South American farm types (Mendelsohn and Seo 2007). This paper extends these early efforts to look at the choice of farm type in Africa. We examine five possible farm types: crop-only rainfed, crop-only irrigated, mixed (both crop and livestock) rainfed, mixed irrigated, and livestock-only farms. We rely on a multinomial logit regression to estimate the link between farm type choice and climate and other exogenous variables. We then estimate the conditional income from each farm type controlling for selection bias (following Heckman 1979 and Dubin and McFadden 1984). We carefully choose seasonal water flow and price variables to identify the choice equation (Ekeland, Heckman, and Nesheim 2002).

We apply the Structural Ricardian Model to study African agriculture. This is an important application because many millions of Africans depend on local farms for income and African agriculture is expected to be very sensitive to climate change We estimate the model using economic surveys collected through a GEF/World Bank project of over 9,000 farms across ten countries in Africa (Dinar et al. 2008). The results reveal that both farm type choice and conditional incomes are sensitive to climate.

We then use the estimated model to predict the impact of climate change on African income. We compare two measures. In one case we assume farm choice is fixed (Schlenker et al 2005) and in the other case, we allow farmers to endogenously adjust farm choice to maximize their net revenue. By comparing the two results, we are able to demonstrate that farm type adaptation will significantly reduce the predicted damages of climate change in Africa.

In the following section, we develop the theory behind the structural Ricardian approach. The third section is devoted to the description of the data. Empirical results and simulation results for 2060 are presented in the fourth and fifth sections. The paper concludes with a discussion of results and policy implications.

2. Theory

The structural Ricardian model is a micro econometric model in which an agent makes a choice from multiple alternatives in the first stage, and maximizes net revenues in the second stage conditional on the choices (Seo and Mendelsohn 2007). Farmers choose from one of the following farm types: crop-only dryland farm, crop-only irrigated farm, mixed (both crops and livestock) rainfed farm, mixed irrigated farm, and livestock-only farm. For each farm type, the farmer considers the inputs and outputs that would maximize net revenue where net revenue is defined broadly to include own consumption. We assume that the farmer then chooses the farm type that maximizes net revenues.

More formally, each farmer maximizes profit by choosing a farm type j (j=1, …, 5):

$$\pi_1 = X\beta_1 + u_1 \tag{1}$$

$$\pi_j^* = Z\gamma_j + \eta_j, \qquad j=1,\ldots, J. \tag{2}$$

where $E(u_1 \mid X, Z) = 0$ and $\mathrm{var}(u_1 \mid X, Z) = \sigma^2$. The subscript j is a categorical variable indicating the choice among J alternatives. The vector Z represents the set of explanatory variables for all the alternatives and the vector X contains the determinants of the variable of interest. Without loss of generality, the profit for alternative 1 is observed only if it is chosen, which happens when

$$\arg\max_{j} \{\pi^*_1, \pi^*_2, ..., \pi^*_J\} = 1. \tag{3}$$

Or

$$\pi_1^* > \pi_k^* \ \text{ for } \forall \text{ k} \neq 1 \text{ [or if } \eta_k - \eta_1 < Z\gamma_1 - Z\gamma_k \ \text{ for k} \neq 1] \tag{4}$$

The probability P_1 of the first farm type being chosen is

$$P_1 = \Pr[\eta_k - \eta_1 < Z\gamma_k - Z\gamma_1] \ \forall \text{ k} \neq 1 \tag{5}$$

Assuming η_j is independently and identically Gumbel distributed, the probability that the farmer will choose farm type 1 among the 5 farm types is (McFadden 1981):

$$P_1 = \frac{\exp(Z\gamma_1)}{\sum_{k=1}^{5} \exp(Z\gamma_k)} \quad . \tag{6}$$

The choice equation is identified using cross prices and seasonal water flows (Brown and Rosen 1982, Ekeland, Heckman, and Nesheim 2002). The parameters are estimated by Maximum Likelihood Method using an iterative nonlinear optimization technique.

Given the choice of the farm type 1, the farmer will choose inputs and outputs to maximize the net revenue from the chosen farm type. The maximum profits can be estimated as a function of exogenous variables X directly from equation 1 above. However, it is likely that the errors in equation 1 and equation 2 are correlated. As profits are only observed for the farms that chose farm type 1, selection bias should be corrected to obtain consistent estimates of the parameters (Heckman 1979). Following Dubin and McFadden (1984), we assume the following linearity condition:

$$E(u_1 | \eta_1,...,\eta_J) = \sigma \cdot \sum_{j=1}^{J} r_j \cdot (\eta_j - E(\eta_j)), \quad \text{with} \ \sum_{\mathrm{j=1}}^{\mathrm{J}} r_j = 0 \tag{7}$$

We can the estimate the conditional profit function for farm type 1 as follows:

$$\pi_1 = X_1 \varphi_1 + \sigma \cdot \sum_{k \neq 1}^{5} r_k \cdot \left[\frac{P_k \cdot \ln P_k}{1 - P_k} + \ln P_1 \right] + \delta_1 \tag{8}$$

Note that η in equation 2 and δ in equation 8 are now independent.

The regressors in the above equation include soils, climate, and socio-economic variables such as the provision of electricity. Country dummy variables are also tested to see if country specific conditions make a substantial difference. We follow the previous studies in specifying the functional form of the equation as a quadratic form.

The expected value of the farm, W, is the sum of the probabilities of each farm type times the conditional land value of that farm type. That is:

$$W(C) = \sum_{k=1}^{5} P_k(C) * \pi_k(C) \tag{9}$$

Note that this measure does not assume a farm will remain as one type. The change in welfare, ΔW, resulting from a climate change from C_A to C_B can be measured as follows.

$$\Delta W = W(C_B) - W(C_A) \tag{10}$$

This change in welfare captures both changes in the probability a farm will be a particular type and the conditional value it would have as that type.

3. Description of the Data

The data for this study came from the recently completed GEF/World Bank project in Africa (Dinar et al. 2008). The surveys asked questions about both crop cultivation activities and livestock management during the farming period from July 2001 to June 2003. The countries were chosen to reflect a wide range of agro-ecological systems in Africa. Niger, Burkina Faso, Senegal, and Ghana were chosen from West Africa; Kenya, Ethiopia, and Cameroon from East Africa; South Africa and Zambia from Southern Africa; and Egypt from North Africa. Zimbabwe was also surveyed but the turmoil in that country during the survey period forced us to drop the observations. The number of surveys varied from country to country (Dinar et al 2008).

In each country, districts were chosen to get a wide representation of farms across climate conditions in that country. In each chosen district, a survey was conducted of randomly selected farms. The sampling was clustered in villages to reduce sampling costs. After cleaning, over 9000 observations remained.

Data on climate were gathered from two sources. We relied on temperature data from satellites operated by the US Department of Defense (Basist et al. 2001). These polar orbiting satellites pass above each location on earth between 6am and 6pm every day. These satellites are equipped with sensors that measure surface temperature by detecting microwaves that pass through clouds (Weng and Grody 1998). The precipitation data come from the Africa Rainfall and Temperature Evaluation System (ARTES) (World Bank 2003). This dataset, created by the National Oceanic and Atmospheric Association's Climate Prediction Center, is based on ground station measurements of precipitation.

Soil data were obtained from FAO (2003). The FAO data provide information about the major and minor soils in each location as well as slope and texture. Data concerning the hydrology were obtained from the University of Colorado (Strzepek and McCluskey 2006). Using a hydrological model for Africa, the hydrology team calculated flow through each district in the surveyed countries. Data on elevation at the centroid of each district were obtained from the United States Geological Survey (USGS 2004). The USGS data are derived from a global digital elevation model with a horizontal grid spacing of 30 arc seconds (approximately one kilometer).

4. Empirical Results

Africa contains a wide range of agricultural ecological zones across the continent. Due to its diverse ecological zones, farmers are expected to rely on different farm types, crops, livestock, inputs, and outputs depending upon the characteristics of the farm location. Table 1 describes how farmers chose different farm types in the sample. Livestock was chosen in about 65 percent of the total farms. Irrigated farms account for about 25 percent of farmers. Across the sample, the proportion of each of the five distinct farm types is: crop-only rainfed farms (28 percent), crop-only irrigated farms (10 percent), mixed rainfed farms (42 percent), mixed irrigated farms (14 percent), and livestock-only farms (6 percent).

We examine whether the choice of these farm types is sensitive to climate. We begin by examining a cross section of farmers who face different climate conditions. We hypothesize that farm type choice is influenced by climate. Table 2 shows the results from a multinomial logit regression of the five farm types against a set of independent variables which include climate variables in quadratic form, soil variables, household characteristics, water flow, pasture, and output prices. The choice of livestock-only is omitted as the base case. Several control variables are significant. When the farm has electricity, farmers favor livestock-only farms over other choices. This may be because electricity is needed for milk production and for storage of livestock products or it may be because electricity is correlated with other missing variables that favor livestock. When Lithosol soils are dominant in a district, farmers tend to choose mixed rainfed farms more often but when Vertisol soils are dominant, farmers choose mixed irrigated farms less often. The remaining soil coefficients, however, are not significant in the choice of farm type. West African farmers are more likely to choose crop-only or mixed irrigated farms and less likely to choose livestock-only farms. This regional parameter is likely picking up the prevalence of livestock diseases in this region. Although other regional dummies were tested, they were not significant. The overall model is highly significant according to the Likelihood Ratio test statistic.

Farm type choices are identified by the prices of maize and millet, and water flows to a district in the spring and in the summer (Brown and Rosen 1982, Ekeland, Heckman, and Nesheim 2002). Note that the water flow is not to the farm itself but rather to the district in which the farm is located[4]. When the water flow in spring is high, farmers are more likely to irrigate their land. When the summer flow is high, then they are more likely to choose rainfed agriculture. Many crops in Africa are planted relatively early in the year so that having water available in spring is critical. When the maize price is high, farmers tend to avoid mixed irrigated farms. Maize is often grown in rainfed farms in Africa. When the millet price is high, farmers choose livestock-only farms more often. If millet is hard to raise, the land may be more suitable for livestock.

The most important result in Table 2 concerns the climate coefficients. The results indicate that climate variables play an important role in the choice of farm types. The choice of crop-only rainfed farms is sensitive to summer temperature and winter precipitation while that of mixed rainfed farms is sensitive to summer temperature, summer precipitation, and winter precipitation. The choice of crop-only irrigated farms is sensitive to all climate variables whereas mixed rainfed farms are sensitive to every climate variable except winter temperature.

Because it is difficult to interpret the quadratic coefficients, we calculate the marginal change in the choice of each farm type at the mean as climate changes in Table 3. If temperature increases by 1 degree Celsius, farmers switch away from crop-only farms or livestock-only farms to mixed farms. By having both crops and livestock, farmers can offset some harm done by natural conditions. If rainfall increases, farmers are more likely to choose crop-only rainfed farms and reduce irrigated farms and livestock-only farms. Higher rainfall allows farmers to avoid the high cost of irrigation and to reap the high profits of crops over livestock.

Once a farmer has selected a farm type, he will choose the optimal level of inputs and

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[4] The paper uses surface water availability for each district. However, climate change might affect the availability of ground water as well (Correspondence with Zilbermann 2008)

outputs to maximize conditional net revenues from the chosen farm type. We estimate conditional net revenue regressions in Table 4 for each farm type. We remove potential selection biases by introducing a set of selection bias variables (Heckman 1979, Dubin and McFadden 1984) and then using OLS. The five regressions reveal that several control variables are significant. Although soils were not generally significant in the choice of farm types, soils do influence conditional net revenues. Crop-only rainfed farms earn lower incomes if they have Lithosol soils. When the soil type is Verisols, crop-only irrigated farms or crop-only rainfed farms earn lower incomes. West African farmers earn more profit when they are crop-only rainfed farmers while they earn less when they are mixed rainfed farmers. Having electricity improves farm incomes for all farm types, but especially that of mixed irrigated farms.

The five regressions in Table 4 reveal that both temperature and precipitation variables are significant determinants of conditional incomes. The shape of the conditional income response to seasonal climate variables, however, is complex and certainly not linear. Quite often the response is concave to one season and convex to the other. The convexity of the response also is in one direction for rainfed farms and in the opposite direction for irrigated farms.

The regressions correct for selection bias using cross selection terms (not own terms). The coefficients on these terms show how the errors in the choice equation are related with the errors in the conditional income regressions. Many of the coefficients are significant suggesting that selection bias is present in the sample. The positive coefficient for the mixed-irrigated farm selection in the crop-only rainfed regression implies that farms which are predicted to be mixed-irrigated earn higher profits than the other crop-only rainfed farms. By contrast, the livestock-only farm selection coefficient is negative in both the crop-only rainfed and mixed rainfed farm equations implying that farms that were predicted to be livestock-only earn lower net revenues than other farms. The livestock-only farm selection coefficient is positive only in the mixed irrigated farm regression.

Table 5 calculates the marginal effects of climate changes on conditional net revenues at the mean climate of the sample. In general, the marginal net revenue results in Table 5 support the marginal choice results in Table 3. If a climate change increases (decreases) the relative income from a specific farm type, that farm type is more (less) likely to be chosen by farmers. For example, as precipitation increases, the net revenue from rainfed farms increases and the net revenue from irrigated farms drops. In Table 3, we see farmers choose rainfed farms more often and irrigated farms less often. As temperature increases, the net revenue from crop-only rainfed farms falls and so does the probability of choosing this farm type. With warmer temperatures, farmers earn more net revenue from mixed irrigated farms and so farmers shift to this farm type. The only exception where the sign of the change in net revenue is different from the sign of the change in choice probability concerns the temperature effect on crop-only irrigated farms. Warming is predicted to increase the net revenue but reduce the chance this farm type is chosen. It is possible that this odd result is due to the inclusion of Egypt in the sample, where despite the relatively moderate temperatures along the Nile, every farm is irrigated.

5. Forecasting Climate Change Impacts and Adaptations

The analysis in the previous section provides ample evidence that climate affects the choice and conditional incomes of each farm type. As climate change unfolds in the coming century, these choices and incomes from each of these farm types are expected to change across Africa. In this section, we simulate the changes in the probability and conditional income of each farm type for different climate scenarios. Farm type choice changes will hinge on many factors such as economic development, technological change, agricultural policy, and international trade. The current model assumes these factors remain unchanged. We consequently are not predicting what the future will look like but rather just trying to understand the role of climate change. In order to make serious predictions of future outcomes, it is important that future studies take account of changes in these other factors.

We examine a set of climate change scenarios predicted by Atmospheric-Oceanic General Circulation Models to provide a range of estimates that are consistent with the predictions in the most recent IPCC (Intergovernmental Panel on Climate Change) report (IPCC 2007). Specifically, we use the A1 scenarios from the following three models: CCC (Canadian Climate Centre) (Boer et al. 2000), CCSR (Centre for Climate System

Research) (Emori et al. 1999), and PCM (Parallel Climate Model) (Washington et al. 2000). Table 6 presents the average seasonal mean temperatures and precipitations predicted by these three climate models for Africa for the year 2060, half a century later. The PCM scenario is a relatively mild and wet outcome with 1.5 degree increase in temperature and 5 percent increase in rainfall. The CCC scenario is a hot and dry outcome with 3.5 degree Celsius increase in temperature and 10 percent decrease in rainfall. The CCSR scenario is between the other two predictions. In addition to these continental level changes, the predictions, especially of rainfall changes, for individual countries vary slightly from the continental average for each climate scenario.

We then simulate the changes in the probability of each farm type given each climate scenario. The results in Table 7 show that under the PCM scenario, rainfed farms, both crop-only and especially mixed, are predicted to increase while irrigated farms, both crop-only and especially mixed, and livestock-only farms decrease. These changes are mainly due to the effects of increasing rainfall under this scenario. The results of the CCSR scenario are similar but not identical to those of the PCM scenario. With the CCSR scenario, the effects on mixed rainfed and irrigated farms are smaller. The results under the CCC scenario differ markedly. With the hot and dry CCC scenario, farmers move away from specialized farms such as crop-only or livestock-only farms towards mixed farms, both rainfed and irrigated. These results reveal that the distribution of future farm types across Africa will change and the change will depend greatly on the climate scenario.

Table 8 shows the results of the simulated changes in conditional net revenue for each farm type and climate scenario. The changes in conditional net revenues support the changes in the choice probabilities in Table 7. The net revenues of crop-only rainfed farms and mixed rainfed farms increase propelling farmers to choose these farm types more often in the PCM scenario. Note that although the net revenues of mixed irrigated farms also increased with the PCM scenario, the increase was relatively small compared to other choices. Consequently, farmers shifted away from mixed irrigation. With the CCSR scenario, the conditional revenue results are also consistent with the direction of farm type choices. The only odd result is that the model predicts a very large reduction in the net revenue from mixed irrigation but only a relatively small reduction in frequency. Under the CCC scenario, the net revenues of mixed rainfed farms increase, but the net revenues of livestock-only farms and crop-only irrigated farms fall. Consequently farmers move away from the specialized farm types in favor of mixed farms that have both crops and livestock.

We next examine the final impacts of climate change assuming that farmers do not change farm type. That is, we adopt the assumption of many existing studies of climate impacts that assume farmers continue to choose their current farm type as climate changes (Rosenzweig and Parry 1994, Schlenker et al. 2005, Deschenes and Greenstone 2007). We multiply the current probability of each farm type for each district times the predicted conditional income for each climate scenario. These “exogenous model” results are shown in Table 9. With the CCC scenario, farmers will lose up to 75 percent of their incomes. With the CCSR scenario, the expected losses climb to 100 percent of their income. Only with the PCM scenario is there a predicted beneficial effect with a 65 percent increase in expected income.

We contrast the “exogenous model” results with the Structural Ricardian results that include the choice of farm type, the “endogenous model” results in Table 9. The endogenous model results combine the results from Table 7 and Table 8 to estimate the changes in the expected income for African farmers. Currently, African farmers earn about 550 USD per hectare of farmland. With the CCC scenario, farmers are expected to lose 40 percent of their incomes in contrast to the 70 percent predicted by the exogenous model. With the CCSR scenario, farmers in some countries get large gains which offset the large losses of farmers in other countries. In contrast, the exogenous model predicts that both sets of farmers lose because conditions change. By allowing farmers to shift to more profitable farm types, the endogenous model predicts far smaller impacts than the potential effects predicted by the exogenous model. Even in the case of the PCM scenario, the endogenous model predicts a smaller benefit because the exogenous model overestimates the potential gains from choices farmers will move away from.

6. Conclusion and Policy Discussion

This paper provides a new econometric method to measure the impacts and adaptations to climate change on African agriculture. The Structural Ricardian technique is used to explain farmers' choice of different farming types and their subsequent conditional net revenues. Special care is taken to allow this choice to be endogenous and to remove sample selection biases. The model is estimated from the data obtained from individual farmers across 10 countries in Africa.

The results reveal that farmers currently choose farm types depending on climate and other exogenous variables such as soils, water flows, household characteristics, and prices. Higher temperatures encourage farmers to adopt mixed farming and avoid specialized farms such as crop-only farms or livestock-only farms. Increases in precipitation induce farmers to rely on rainfed versus irrigated crops.

The analysis of conditional net revenues supports the results from the choice model of farm types. As temperatures warm, farm net revenues from crop-only farms or livestock-only farms fall whereas net revenues from mixed farms increase. With precipitation increases, farm net revenues from irrigated farms fall and net revenues from rainfed farms increase. These changes in net revenues encourage farmers to change their choice of farm type.

The model is then used to simulate how climate might affect future farm type choices and conditional net revenues. Different climate scenarios are explored to reveal a plausible range of outcomes by 2060. With the mild wet PCM climate scenario, Africa is predicted to have more rainfed farms and less irrigated farms and livestock-only farms. Under the very hot and dry CCC climate scenario, farmers are expected to choose mixed farms more often and crop-only irrigated farms or livestock-only farms less often. The results from the CCSR scenario are similar to those from the PCM scenario except that there are smaller changes in mixed farms. The net revenues generated by each farm type would shift in a comparable fashion. Under the PCM scenario, the net revenues of rainfed crop-only farms would increase causing farmers to shift to crop-only rainfed farming. There is also a large shift from mixed irrigated to mixed rainfed farms in the PCM scenario. With the CCSR scenario, there is still an increase in crop-only rainfed farms but the changes in mixed farms are smaller. In contrast, under the CCC scenario, there is a decrease in the net revenues for all farm types except mixed rainfed farming causing farmers to shift towards mixed rainfed farms in the future.

Putting all the information together, we calculated the expected impacts of climate change on African agriculture. If farm types are assumed to be fixed and unchanging, farmers are predicted to lose 75 percent of their income under the CCC scenario and over 100 percent of their income under the CCSR scenario. However, when the model takes into account the endogenous adaptation decisions of farmers, farm income is predicted to fall by 40 percent under the CCC scenario and not at all under the CCSR scenario. Omitting adaptation seriously overestimates the damages of climate change.

In conclusion, the Structural Ricardian model reveals that adaptation is a critical facet of impact estimation. Farmers and other economic agents who will be impacted by climate change will adapt to reduce the potential harm. It is important that analysts take these adaptations into account or they may dramatically overestimate climate damages. Understanding adaptation is also important for its own sake as governments consider how they may assist in helping efficient adaptations to take place. Adaptations must be made to fit local conditions and so will have to be designed carefully to vary as needed across the landscape.

In addition to the many changes that farmers can make for themselves, government can also make significant contributions to adaptation. First, they can conduct research and development that leads to new crops and animals more suited for hotter and possibly dryer conditions. Governments can provide credit to help farmers invest in their land and farming operations. Governments can create and protect private property rights so that farmers have the incentive to autonomously adapt. Governments can provide access to reduce the cost of farmers getting their product to market. Governments can encourage economies to develop and diversify away from agriculture so that only a small fraction of African economies would be at risk from climate change. Finally, if falling productivity leads to some areas being unable to support their populations, governments can help people migrate to more promising opportunities in other regions or perhaps in urban areas.

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Table 1: Number of Farms of Each Type

	Number	Percentage
Crop-only Rainfed	2397	28.4
Crop-only Irrigated	851	10.1
Mixed Rainfed	3517	41.7
Mixed Irrigated	1159	13.8
Livestock Only	503	6.0
Africa Total	8427	100.0

Table 2: Multinomial Logit Model of Farm Type Choice

	Crop Only Rainfed		Crop Only Irrigated	
	Coefficient.	Chi sq	Coefficient.	Chi sq
Intercept	9.833	17.57	12.247	22.53
Summer Temperature	-0.950	34.34	-1.055	30.43
Summer Temperature^2	0.0205	41.32	0.0202	27.58
Summer Precipitation	0.000783	0.02	-0.032	27.41
Summer Precipitation^2	0.000017	0.65	0.000109	20.34
Winter Temperature	0.217	1.64	0.351	4.27
Winter Temperature^2	-0.00576	1.56	-0.00593	1.53
Winter Precipitation	0.0401	22.02	-0.0395	13.13
Winter Precipitation^2	-0.00011	2.73	0.00012	2.16
Electricity	-0.502	24.96	-0.515	16.34
Fluvisol Soil	-2.052	0.38	0.061	0.00
Lithosol Soil	2.554	1.91	-0.742	0.10
Verisol Soil	0.634	0.16	-1.103	0.33
West Africa	-0.142	1.00	1.958	96.11
Maize price	0.505	0.38	-1.586	1.81
Water Flow spring	-2.555	19.51	1.150	2.77
Water Flow summer	0.648	12.09	-0.335	2.07
Millet price	-0.947	1.42	-4.288	14.64

Note: N=7965. Likelihood Ratio Test: P<0.0001

Table 2: Continued.

	Mixed Rainfed		Mixed Irrigated	
	Coefficient.	Chi sq	Coefficient.	Chi sq
Intercept	6.228	7.33	12.048	24.22
Summer Temperature	-0.569	12.70	-1.018	32.64
Summer Temperature^2	0.0128	16.56	0.0196	30.28
Summer Precipitation	0.00314	0.39	-0.0287	23.99
Summer Precipitation^2	-6.48E-06	0.10	0.000118	25.20
Winter Temperature	0.173	1.11	0.268	2.53
Winter Temperature^2	-0.00451	1.01	-0.00266	0.32
Winter Precipitation	0.0261	9.55	-0.0306	5.89
Winter Precipitation^2	-0.00005	0.66	-0.00007	0.35
Electricity	-0.149	2.24	-0.257	4.46
Fluvisol Soil	-0.699	0.05	0.535	0.01
Lithosol Soil	2.282	1.54	-3.105	1.09
Verisol Soil	0.079	0.00	-3.460	1.92
West Africa	-0.048	0.12	2.011	120.02
Maize price	0.919	1.33	-6.462	27.62
Water Flow spring	-2.616	20.65	1.252	3.83
Water Flow summer	0.634	11.60	-0.324	2.27
Millet price	-0.612	0.62	-1.139	1.30

Table 3: Marginal Climate Effects on Farm Type Probability (Percent)

	Crop-Only Dryland	Crop-Only Irrigated	Mixed Dryland	Mixed Irrigated	Livestock-Only
Baseline	26.97	13.00	34.04	22.22	3.76
Temperature (C˚)	-0.81	-0.18	0.03	1.16	-0.20
Precipitation (mm/mo)	0.15	-0.08	-0.02	-0.05	-0.01

Table 4: Conditional Income Regressions

	Crop-only rainfed Coefficient	T stat	Crop-only irrigated Coefficient	T-stat	Livestock-only Coefficient	T stat
Intercept	-515.3	-1.01	-3881.4	-1.58	5491.1	2.41
T sum	61.21	1.50	254.20	1.18	-481.74	-2.32
T sum2	-0.538	-0.66	-2.843	-0.63	9.624	2.25
T win	-41.03	-0.89	100.38	1.38	89.64	1.00
T win2	0.0457	0.04	-5.144	-2.58	-2.942	-1.16
P sum	1.558	1.52	-1.363	-0.29	-9.904	-2.53
P sum2	0.00752	1.93	-0.00775	-0.45	0.07398	4.24
P win	4.707	2.37	-15.55	-0.98	28.04	2.34
P win2	0.0102	0.99	0.0465	0.73	-0.0899	-1.51
Electricity	99.39	1.87	545.31	1.82	33.51	0.16
Fluvisol Soil	687.6	0.91	1611.9	0.55	-819.2	-0.38
Lithosol Soil	-716.3	-3.66	-2604.6	-1.68	1152.1	0.65
Verisol Soil	-1508.1	-4.26	-3004.1	-2.31	764.4	1.02
West Africa	170.59	2.36	-252.91	-0.61	42.87	0.15
Select Crop-only rainfed			-2458.5	-1.04	3558.2	1.81
Select Crop-only irrigated	597.9	2.30			-1185.9	-1.61
Select Mixed rainfed	587.6	1.37	1204.2	0.82	-2025.3	-1.38
Select Mixed irrigated	918.5	4.43	204.8	0.24	-190.2	-0.37
Select Livestock-only	-2470.8	-4.59	676.9	1.28		
N	2397		851		574	
R sq	0.22		0.36		0.28	

Table 4: continued

	Mixed rainfed Coefficient	t	Mixed irrigated Coefficient	t
Intercept	4635.3	6.49	-12835.0	-3.48
T sum	-402.07	-8.65	1991.70	5.82
T sum2	8.155	8.69	-37.946	-5.37
T win	195.49	4.06	-926.55	-6.11
T win2	-4.264	-3.40	21.004	5.65
P sum	-3.029	-2.83	-6.963	-0.96
P sum2	0.03435	8.28	-0.05856	-2.11
P win	13.407	5.99	-104.786	-5.19
P win2	-0.03216	-2.91	0.37361	4.07
Electricity	0.18	0.00	1737.21	4.65
Fluvisol Soil	1152.4	1.38	-8638.2	-1.17
Lithosol Soil	308.5	1.50	-10251.0	-1.65
Verisol Soil	-648.6	-1.47	3310.5	0.68
West Africa	-284.2	-3.34	173.9	0.33
Select Crop-only rainfed	3454.9	11.43	-17158.0	-5.36
Select Crop-only irrigated	321.7	1.50	1319.4	1.02
Select Mixed rainfed			11493.0	4.93
Select Mixed irrigated	515.8	2.78		
Select Livestock only	-3891.9	-10.05	4153.1	2.84
N	3529		1175	
R sq	0.23		0.45	

Table 5: Marginal Effects on Conditional Incomes

	Marginal Effects T ($/°C)	Marginal Effects P ($/mm/mo)	Elasticities T	Elasticities P
Crop-only rainfed	-35.15	26.87	-0.54	1.22
Crop-only irrigated	36.15	-108.74	0.44	-3.27
Mixed rainfed	25.24	14.96	0.39	0.68
Mixed irrigated	9.21	-15.81	0.14	-0.72
Livestock only	-4.55	8.21	-0.07	0.33

Table 6: AOGCM Climate Scenarios

	Current	**2060**
Summer Temperature (°C)		
CCC	25.7	+3.0
CCSR	25.7	+2.7
PCM	25.7	+1.5
Winter Temperature (°C)		
CCC	22.4	+4.0
CCSR	22.4	+2.6
PCM	22.4	+2.0
Summer Rainfall (mm/month)		
CCC	149.8	-21.7
CCSR	149.8	-5.6
PCM	149.8	-11.1
Winter Rainfall (mm/month)		
CCC	12.8	+5.0
CCSR	12.8	+2.7
PCM	12.8	+17.9

Table 7: The Change in Probability of Farm Type by Climate Scenario in 2060 (percent)

	Crop only rainfed	Crop only irrigated	Mixed rainfed	Mixed irrigated	Livestock only
Baseline	26.97	13.00	34.04	22.22	3.76
CCC	+1.21	-2.15	+1.17	+0.73	-0.95
CCSR	+7.21	-2.84	+2.60	-5.94	-1.04
PCM	+6.33	-1.49	+7.41	-10.19	-2.05

Table 8: The Change in Conditional Net Revenue by Climate Scenario in 2060 (USD/yr/ha)

	Crop-only rainfed	Crop-only irrigated	Mixed rainfed	Mixed irrigated	Livestock only
Baseline	423.27	505.20	526.44	529.50	165.14
CCC	-22.54	-328.18	136.99	-367.80	-58.16
CCSR	217.33	-196.04	322.80	-967.33	253.70
PCM	604.24	-382.27	461.91	238.81	191.66

Table 9: Predicted Change in Expected Income by Climate Scenario in 2060 (USD/yr/ha)

(1) Farm Type Exogenous

Scenario	Change	% Change	Lower 95%	Upper 95%
CCC	-415	-75%	-435	-395
CCSR	-628	-114%	-661	-596
PCM	+358	+65%	+281	+434

(2) Farm Type Endogenous

Scenario	Change	% Change	Lower 95%	Upper 95%
CCC	-221	-40%	-233	-210
CCSR	+26	+5%	+13	+38
PCM	+278	+50%	+260	+295

Baseline value is $535 yr/ha. Bootstrapping was used to obtain upper and lower estimates of expected impacts.