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Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management[1]

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Abstract

This article develops a new cross-sectional methodology that explicitly incorporates adaptation into an analysis of the impacts of climate change. The methodology examines how a farmer will change choices of species and number to adapt to climate. The approach is applied to study Africa, where the impacts of climate change are expected to be the most severe. The results indicate that in warmer places, African farmers switch from beef cattle to more heat-tolerant goats and sheep. In wetter places, farmers switch from cattle and sheep to goats and chickens. The results indicate that large commercial livestock operations specializing in beef cattle will be hard hit from climate change whereas small farmers who can easily substitute to goats and/or sheep will be more resilient.

JEL classification: C53, O13, O18, O55, R11

Keywords: Climate change; Africa; Livestock; Cross-sectional adaptation analysis

1. Introduction

This article uses cross-sectional evidence to explore how farmers adapt to exogenous environmental factors such as climate and soils. The model builds on the original insights of the Ricardian model that explored the locus of land value per hectare (Mendelsohn et al., 1994). Although the Ricardian model captures adaptation in its measure of impacts, it does not provide any insight into how farmers adapt. In this article, we develop a new approach, a Structural Ricardian Model, that explicitly models the underlying endogenous decisions by farmers. By comparing choices of farmers who face different conditions, the model uncovers how farmers adapt. Conditional incomes, using a Ricardian approach, are then estimated for each choice made by each farmer.

We develop this new method and then apply it to study how African farmers adapt livestock management to climate. We explore which species they choose, how many animals they own, and how net revenue per animal for each species changes. Understanding adaptation is an important goal in itself to assist planning by policy makers and private individuals. However, understanding adaptation is also important if one is interested in quantifying the impacts of climate change. Forecasts that over- or underpredict adaptation will under- or overpredict the residual damages from climate change.

Climate impact studies have consistently predicted extensive impacts to the agricultural sector from climate change across the globe (Pearce et al., 1996; McCarthy et al., 2001; Tol, 2002). The bulk of agricultural studies on the effect of climate change have focused on crops. However, a large fraction of agricultural output is from livestock. In the United States, livestock account for about 40% of the market value of agricultural products sold (USDA, 2002). Almost 80% of African agricultural land is used for grazing. Yet there are very few economic analyses of climatic effects on livestock. An important exception is the study of the effects of climate change on American livestock (Adams et al., 1999). American livestock appear not to be vulnerable to climate change because most live in protected environments (sheds, barns, etc.) and rely heavily on supplemental feed (e.g., hay and corn). African livestock have no protective structures and they graze off the land. As a result, we anticipate that

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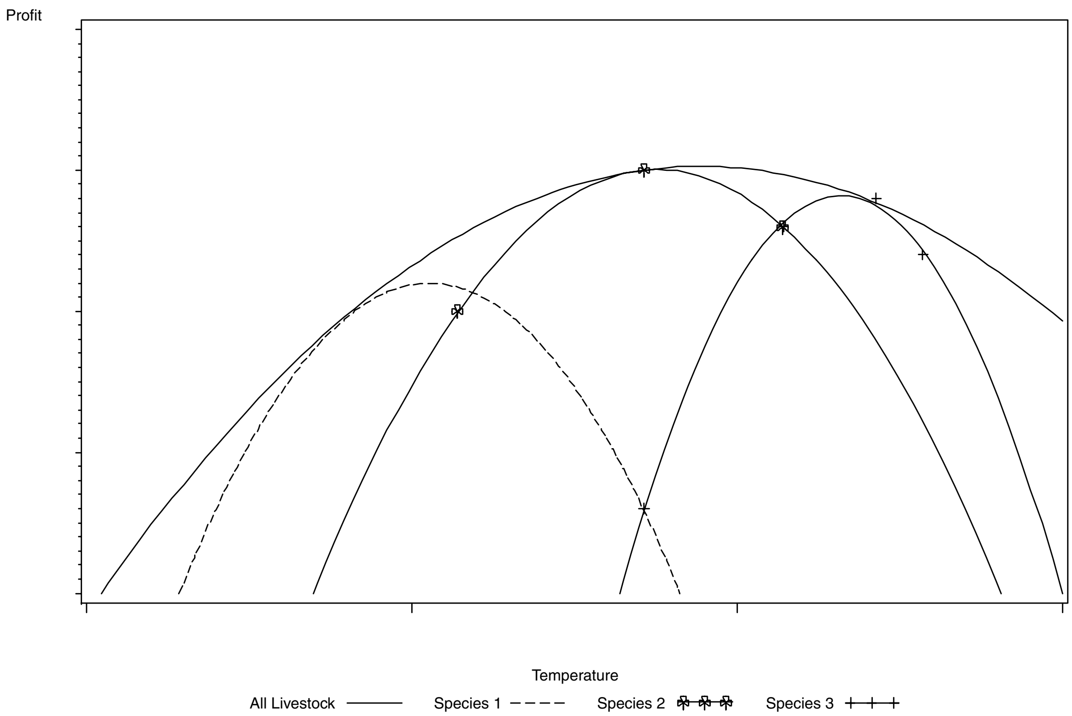

Fig. 1. Theoretical livestock response functions.

African livestock will be sensitive to climate change. In a separate article, the Ricardian model is applied to African livestock data (Seo et al., 2007) and shows that livestock are sensitive to climate. In this article we provide insight into how farmers adjust to climate and what they might do in the future.

The underlying theory of the Structural Ricardian Model is developed in the next section. Section 3 discusses how data were collected from over 5,000 farmers who own livestock in 10 countries across Africa for this study. Section 4 discusses the estimation procedure and the cross-sectional empirical results. Forecasted impacts from three climate change scenarios generated by Atmospheric Oceanic General Circulation Models (AOGCMs) are then examined in Section 5. The article concludes with a summary of results and policy implications.

2. Theory

A farmer's optimization decision can be seen as a simultaneous multiple-stage procedure. The farmer chooses the levels of inputs, the desired number of animals, and the species that will yield the highest net profit. Given the profit-maximizing inputs from each farmer, one can estimate the loci of profit-maximizing choices for each species across exogenous environmental factors such as temperature or precipitation. These are the individual loci that lie beneath the overall profit function for the farm (Mendelsohn et al., 1994). We call the approach a "cross-sectional adaptation model" because it estimates the choice of a specific animal, the number of animals, and the underlying profit response functions per animal for each species that form the overall profit function. For example, in Fig. 1 we display a traditional Ricardian response function with respect to temperature. Underneath the locus of all choices is a set of species-specific response functions. Given the climate, the farmer must choose the most profitable species and also the inputs that will maximize the value of that species. We examine the individual net revenue functions for each species as well as the overall net revenue function across all species. We assume that each farmer makes his animal husbandry decisions to maximize profit.[2] Hence, the probability that a species is chosen depends on the profitability of that animal species (or crop if one wants to examine the crop sector). We assume that farmer i's profit in choosing livestock j ($j = 1, 2, \ldots, J$) is

$$\pi_{ji} = V(Z_{ji}) + \varepsilon_{ji}, \tag{1}$$

where Z is a vector of independent variables that includes climate variables, soils, and other socioeconomic variables such as household characteristics. The profit function in Eq. (1) is composed of two components: the observable component V and an error term ε. The error term is unknown to the researcher, but may be known to the farmer. The farmer will choose the livestock that gives him the highest profit. The farmer will choose

[2] The theory of profit maximization can be contested especially in Africa (De Janvry et al., 1991; Moll, 2005; Singh et al., 1986). We made the following two adjustments to address the issues arising from special situations of African markets. First, we assume that if a farmer consumes his own product, it is valued at market price. Second, most farms depend on their own labor. Although it might be reasonable to value own labor by market wages, empirical examinations did not support any specific wage.

animal j over all other animals if

$$\pi^*(Z_{ji}) > \pi^*(Z_{ki}) \quad \text{for} \quad \forall \mathrm{k} \neq \mathrm{j} \\ \times [\text{or if } \varepsilon_k - \varepsilon_j < V(Z_{ji}) - V(Z_{ki}) \quad \text{for} \quad \mathrm{k} \neq \mathrm{j}]. \tag{2}$$

More succinctly, farmer i's problem is

$$\arg\max_j [\pi^*(Z_{1i}), \pi^*(Z_{2i}), \ldots, \pi^*(Z_{Ji})]. \tag{3}$$

The probability P_{ji} for the *jth* livestock to be chosen is then

$$P_{ji} = \Pr[\varepsilon_k - \varepsilon_j < V_j - V_k] \quad \forall \mathrm{k} \neq \mathrm{j} \text{ where } V_j = V(Z_{ji}). \tag{4}$$

Assuming ε is independently and identically Gumbel distributed[3] and V_k can be written linearly in the parameters

$$P_{ji} = \frac{\exp(Z_{ji}\gamma_j)}{\sum_{k=1}^{J} \exp(Z_{ki}\gamma_k)}, \tag{5}$$

which gives the probability that farmer i will choose livestock j among J animals (Chow, 1983; McFadden, 1981).

The parameters can be estimated by the maximum likelihood method using an iterative nonlinear optimization technique such as the Newton–Raphson method. These estimates are CAN (Consistent and Asymptotically Normal) under standard regularity conditions (McFadden, 1999).

Note that farmers can choose more than one species of livestock among the five species in our study. That is, there are many combinations of livestock species that the farmer could choose. In this analysis, we assume that farmers choose one primary species from the five species. A primary species is defined as that which generates the highest total net revenue for the farm (Train, 2003). In another analysis of livestock choice, we compare this approach using the primary species with an alternative portfolio approach that examines all possible choices including combinations of species (Seo and Mendelsohn, 2007). The two approaches yield similar results.

Conditional on the livestock species chosen, we estimate the optimal number of animals per farm for each species and the net revenue per animal for each species. We rely on a two-stage model. In the first stage, we estimate the probability of selecting a species (Eq. 5). In the second stage, conditional on the choice of a specific species, we estimate the optimal number of that species and the net revenue per animal. We identify the species choice equations using the relative prices of each choice. We identify the number of animal equations using the percentage of grassland in the district. Note that this more general variable was used instead of grassland on the farm because many African livestock owners graze animals on common lands.

Because the profit described in Eq. (1) is observed only for the chosen species, one must correct for possible selection bias when estimating the conditional net revenues or numbers of animals (Heckman, 1979). Since the farmer maximizes net revenue conditional on the choice of that species, the error in the second-stage equation may be correlated with the error in the first stage. According to Dubin and McFadden (1984), with the assumption of the following linearity condition[4]:

$$E(u_j|\varepsilon_1, \ldots, \varepsilon_J) = \sigma \cdot \sum_{j=1}^{J} r_j \cdot (\varepsilon_j - E(\varepsilon_j)), \text{ with } \sum_{j=1}^{J} r_j = 0, \tag{6}$$

where u_j is the error from the profit equation in the second stage, ε_j is the error from the choice equation in the first stage, σ is the standard error of the profit equation, and r_j the correlation between the profit equation and choice equations, then the selection bias-corrected conditional profit functions can be consistently estimated as

$$\pi_j = X_j\varphi_j + \sigma \cdot \sum_{i \neq j}^{J} r_i \cdot \left(\frac{P_i \cdot \ln P_i}{1 - P_i} + \ln P_j \right) + w_j, \tag{7a}$$

where the second term on the right-hand side is the selection bias correction term; X_j is a set of independent variables that include climate variables, soils, and socioeconomic variables; φ_j is a vector of parameters; and w_j is the error term.

The optimal number of animals can be estimated in the same manner:

$$N_j = X_j\eta_j + \sigma \cdot \sum_{i \neq j}^{J} r_i \cdot \left(\frac{P_i \cdot \ln P_i}{1 - P_i} + \ln P_j \right) + \upsilon_j, \tag{7b}$$

where the various terms are defined similarly as in Eq. (7a).

The two-stage model is composed of Eq. (5) and equations (7a) and (7b). Expected net revenue is therefore

$$W_i(Z_i) = \sum_{j=1}^{J} P_j(Z_{ji}) \cdot \pi_j(Z_{ji}) \cdot N_j(Z_{ji}). \tag{8}$$

Because climate is an independent variable in all three terms in Eq. (8), the marginal effect on welfare of a change in a climate variable, say Z_c, has three components: the effect on the probability of the livestock to be chosen, the direct effect on the conditional profit per animal, and the effect on the conditional number of animals:

$$\frac{\partial W_j}{\partial z_c} = \frac{\partial P_j}{\partial z_c} \cdot \pi_j \cdot N_j + \frac{\partial \pi_j}{\partial z_c} \cdot P_j \cdot N_j + \frac{\partial N_j}{\partial z_c} \cdot P_j \cdot \pi_j, \tag{9}$$

[3] Two common assumptions about the error term are either the Normal or the Gumbel distribution. Normal random variables have the property that any linear combination of normal varieties is normal. The difference between two Gumbel random variables has a logistic distribution, which is similar to the normal but with larger tails. Thus the choice is somewhat arbitrary with large samples (Greene, 1998).

[4] See Bourguignon et al. (2004) for the details of the selection bias corrections from the multinomial choice. They find that in most cases, Dubin and McFadden's method is preferable to the most commonly used Lee method, as well as to Dhal's semiparametric method. Monte Carlo experiments show that selection bias correction based on the multinomial logit model can provide fairly good correction for the outcome equation even when the IIA hypothesis is violated.

where the marginal effect on the probability can be obtained by differentiating Eq. (5):

$$\frac{\partial P_j}{\partial z_c} = P_j \left[\gamma_j - \sum_{k=1}^{J} P_k \gamma_k \right], \tag{10}$$

and the marginal effect on the net revenue per animal, assuming a quadratic relationship between the net revenue and the corresponding climate variable, can be obtained by differentiating Eq. (7a):

$$\frac{\partial \pi_j}{\partial z_c} = \varphi_{j1} + 2 \cdot \varphi_{j2} \cdot z_c, \tag{11}$$

and the marginal effect on the number of animals per farm, also assuming a quadratic relationship between the number of animals and the relevant climate variable, can be found by differentiating Eq. (7b):

$$\frac{\partial N_j}{\partial z_c} = \eta_{j1} + 2 \cdot \eta_{j2} \cdot z_c, \tag{12}$$

where the subscripts 1 and 2 in equations (11) and (12) denote the estimated parameters for the linear term and the quadratic term for the climate variable z_c.

The change in welfare resulting from a nonmarginal change in climate can be computed as the difference in the expected net revenues in the two states before and after climate change. Suppose that climate changes from C_{before} to C_{after}. Then the change in welfare can be approximated as

$$\Delta W_i = W_i(C_{\text{after}}) - W_i(C_{\text{before}}). \tag{13}$$

The uncertainty surrounding our measure of the welfare change can be described by the 95% confidence interval of the expected climate change impact. In principle, there are two ways to calculate confidence intervals: parametric and nonparametric. It is difficult to calculate the variance of the climate change impact parametrically in this model because welfare is the product of three predictions. We provide uncertainty estimates in this study via a bootstrap method by resampling 200 times from the original sample and calculating the 95% confidence interval using the mean and the standard deviation of the resulting climate change impacts (Andrews and Buchinsky, 2000).

3. Data

Data for this study come from a larger Global Environmental Facility (GEF)–World Bank project to study climate change impacts on agriculture in Africa (Dinar et al., 2008). The countries included were Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, and Zambia. (Zimbabwe had to be dropped from the livestock analysis because of turbulent conditions in that country during the survey.) The countries were selected to represent the wide range of climate throughout Africa. Districts within each country were selected to provide as much within-country climate variation as possible. Because existing economic data were not sufficient to support an analysis, an economic survey of farmers was conducted. The original survey interviewed more than 9,000 farmers from 11 countries. Within that sample, more than 5,000 were livestock farmers (Kurukulasuriya et al., 2006).

The livestock data include information on species, the stock of livestock owned, and the livestock products and animals sold during the period of July 2002 to June 2003 (the data from Kenya, Ethiopia, and Cameroon cover the period July 2003 to June 2004). The data identify the five major types of livestock in Africa as beef cattle, dairy cattle, goats, sheep, and chickens. Other less frequently recorded animals include pigs, breeding bulls, oxen, camels, ducks, guinea fowl, horses, bees, and doves. The major livestock products sold were milk, meat, eggs, wool, and leather. Other products included butter, cheese, honey, skins, and manure. The five major livestock accounted for 93% of the total net livestock revenue in the sample (Seo and Mendelsohn, 2007).

All countries in the sample had a large number of livestock farms. Most of the farms in our survey were small household farms, but a majority of the farms in South Africa and Kenya located in temperate climate zones were large commercial farms. Definitions of what constitutes a small household farm versus a large commercial farm are country-specific. South Africa had a large number of commercial beef cattle farms while Kenyan farmers kept dairy cattle and beef cattle in large numbers. Farmers in Egypt tended to raise chickens while West African farmers depended more on goats and sheep (Seo and Mendelsohn, 2007).

Climate data come from two sources: U.S. Defense Department satellites and weather station observations. We relied on satellite temperature observations and interpolated precipitation observations from ground stations (see Mendelsohn et al. [2007] for a detailed explanation). The climate data measures the long-run average weather (17 to 30 years), not the weather in the particular year of the economic survey. Climate data were gathered in monthly measures of temperature (°C) and precipitation (mm/month) and then aggregated by season: Winter (May, June, July), Spring (August, September, October), Summer (November, December, January), and Fall (February, March, April). Seasons for locations north of the equator were defined in reverse. Soil data were obtained from the FAO digital soil map of the world (Food and Agriculture Organization [FAO] 2004). Soil data were extrapolated to the district level using GIS. The data set reports 116 dominant soil types and 26 aggregated soil types.

4. Empirical results

As indicated above, although there are many livestock species in Africa, we focus on the five primary species that

Table 1
Multinomial logit species selection model

Variable	Beef cattle			Dairy cattle			Goats			Sheep		
	Estimate	χ^2	Odds ratio	Estimate	χ^2	Odds ratio	Estimate	χ^2	Odds ratio	Estimate	χ^2	Odds ratio
Intercept	5.94	5.58		10.85	45.7		−0.22	0.01		4.92	6.85	
Temperature summer	0.31	2.82	1.37	−0.942	76.5	0.39	−0.168	1.74	0.85	−0.105	0.68	0.90
Temperature summer sq	−0.0047	1.62	1.00	0.0157	53.3	1.02	0.0049	3.79	1.01	0.0023	0.83	1.00
Precipitation summer	0.0058	0.94	1.01	−0.0201	27.6	0.98	−0.0119	8.54	0.99	−0.0155	12.7	0.99
Precipitation summer sq	0.0000	0.22	1.00	0.0001	12.6	1.00	0.0001	14.4	1.00	0.0000	3.03	1.00
Temperature winter	−1.18	73.7	0.31	0.296	5.41	1.35	0.0755	0.16	1.08	−0.435	8.63	0.65
Temperature winter sq	0.0284	52.6	1.03	−0.0036	1.17	1.00	0.0003	0.00	1.00	0.0139	12.07	1.01
Precipitation winter	0.020	5.53	1.02	0.0065	1.44	1.01	−0.0178	8.98	0.98	−0.0243	14.5	0.98
Precipitation winter sq	−0.0001	1.52	1.00	−0.0001	5.98	1.00	0.0001	5.07	1.00	0.0000	0.22	1.00
Soil Cambisols	1.09	1.30	2.97	1.59	7.04	4.93	0.503	0.79	1.65	0.6404	1.33	1.90
Soil Gleysols	−1.86	1.17	0.16	−7.35	25.1	0.00	−2.63	4.23	0.07	−3.67	5.90	0.03
Electricity	0.96	18.3	2.60	−0.078	0.19	0.93	0.0658	0.16	1.07	0.336	4.23	1.40
Beef cattle price	−0.0027	10.06	1.00	0.0002	0.07	1.00	−0.0016	3.32	1.00	−0.0033	16.1	1.00
Milk price	−0.482	11.25	0.62	0.511	24.4	1.67	0.0489	0.20	1.05	−0.0323	0.09	0.97
Goat price	0.0212	5.10	1.02	0.0136	3.92	1.01	−0.0180	3.90	0.98	−0.0261	8.31	0.97
Sheep price	0.0066	1.85	1.01	0.0034	0.79	1.00	−0.0085	2.57	0.99	−0.0037	0.53	1.00
Chicken price	−0.513	14.4	0.60	−1.074	142	0.34	0.416	18.9	1.52	0.765	66.5	2.15

Notes: (1) The base case is chickens.
(2) The critical value of chi-square statistic for the significance at 5% is 3.7.
(3) Three tests of global significance of the model: Likelihood ratio test: $P < 0.0001$, Lagrange multiplier test: $P < 0.0001$, and Wald test: $P < 0.0001$.

generated the most livestock income: beef cattle, dairy cattle, goats, sheep, and chickens.[5] We model the probability of choosing each species as a function of summer and winter temperature and summer and winter precipitation. We also include other explanatory variables such as dominant soils and a dummy variable for electricity. We identified the selection equations by the input and output prices of the five species. For example, the higher the price of milk (one of the primary outputs) the more likely farmers are to choose dairy cattle and goats, but the less likely they are to choose sheep and beef cattle.

Table 1 shows the results of the multinomial logit regression of the probability of choosing each of the five species. The base case is a household that chose chickens. Most of the coefficient estimates are significantly different from zero. The three tests of the global significance of the model—likelihood ratio test, Lagrange multiplier test, and Wald test—verify that the model is highly significant. The coefficients report the odds ratio. For example, the odds ratio of the electricity dummy for beef cattle is 2.6, which implies that farms with electricity are 2.6 times (odds ratio) more likely to own beef cattle than farms without electricity. Farms with electricity are also more likely to choose sheep but less likely to choose dairy cattle and goats. Soil variables are weakly significant and their coefficients vary across livestock species. For example, dairy cattle are more likely to be chosen under Cambisol soils, but not under Gleysol soils. Under Gleysol soils, beef cattle are more likely to be selected, compared with other species.

[5] Species can be further differentiated by breeds (Oklahoma State University, 2007). For example, some breeds of beef cattle and sheep are more heat tolerant than others. Information about breeds was not collected in the survey and so this study does not distinguish between different breeds within species.

Coefficients for livestock prices are significantly different from zero in most cases. As the price of milk, the primary output from dairy cattle and goats, rises, more farmers choose dairy cattle and goats. Own animal price was difficult to interpret because it is both the price of buying an animal (input price) and the price of selling it (output price). In general, higher own prices led farmers away from choosing a species. For example, higher beef cattle prices discouraged farmers from selecting beef cattle. Cross price effects are also evident in Table 1. Negative cross price terms imply that two animals are incompatible whereas positive cross price terms imply that they can be raised jointly. For example, the coefficient on the price of goats (chickens) is positive (negative) for beef and dairy cattle but negative (positive) for sheep, implying that goats (chickens) can be raised with cattle (sheep) but not sheep (cattle).

Most climate variables are significantly different from zero. The quadratic summer temperature coefficients are positive for goats, sheep, and dairy cattle implying a U-shaped function but the temperature response function for beef cattle is hill-shaped. The quadratic coefficients of the precipitation variables are generally positive, indicating a U shape except for beef cattle and dairy cattle responses to winter precipitation. Although not shown in Table 1, we also tested for the effects of other important control variables such as water availability, altitude, and other social factors such as religion. These variables were dropped because they were not significant. We also tested a number of variables describing the farmer including gender, age, and education but these too were not significant and so were dropped.

Fig. 2a graphs the relationship between the probability of choosing a species and annual temperature. Note that the mean temperature in sub-Saharan Africa is 22°C. The probability of choosing beef cattle and dairy cattle decreases rapidly as temperature rises. In contrast, the probability of choosing goats and sheep climbs as temperature rises. With chickens, the estimated probability is hill-shaped, with a maximum at the current mean temperature of Africa. The graph clearly reveals that farmers in Africa today choose animal species selectively to make the best use of the current temperature.

Fig. 2b displays the estimated relationship between the probability of choosing a species and annual precipitation. The probability of choosing beef cattle, dairy cattle, and sheep all decreases as precipitation increases. Greater rainfall increases the probability of diseases such as Trypanosomiasis (Nagana), Theileriasis (East Coast Fever), and Rift Valley Fever (Ford and Katondo 1977; University of Georgia, 2007) and, perhaps more importantly, in the long term, shifts the ecosystem from savanna to forest (Sankaran et al., 2005). All three of the large grazing animals are clearly more productive in grasslands. In contrast to the above results, goats and especially chickens are more likely as rainfall increases. Goats may be relatively better able to forage successfully in forest settings.

In the second stage of the analysis, we estimate the conditional net revenue functions. The net revenue per animal for each chosen species is regressed on climate variables, soil variables, a dummy variable for electricity, and sale price of the corresponding livestock. We identify these net revenue regressions by the sale prices. We account for selection bias by using the Dubin–McFadden selection bias correction terms. These conditional net revenue regressions use the same seasonal climate variables used in the choice regressions. The functional form is quadratic in both temperature and precipitation.

Table 2 summarizes the results of the regression of the conditional net revenue per animal. These regressions confirm that the conditional net incomes from the five livestock are sensitive to climate. For beef cattle and chickens, the linear terms for summer temperature are positive and quadratic terms are negative, implying a hill-shaped response function. For goats and dairy cattle, the response functions are U-shaped, but the coefficients of the second-order terms are not significant. Summer precipitation response functions for all the species are U-shaped. Some soil variables are significant. Gleysol soils are especially harmful to dairy cattle, but beneficial to sheep. The price of dairy cattle, goats, chickens, and sheep have a positive own price elasticity while the own price elasticity of beef cattle is insignificant.

The selection bias coefficients reveal interactions among the species. If the coefficients are negative (positive), they suggest that conditions which make the farm attractive to one species would make it less (more) attractive to the other. For example, in the beef cattle income regression, the coefficient on the selection term for sheep is positive, but the selection term for chickens is negative. The results reveal that farmers who the selection model predicted would choose sheep (but who actually chose beef cattle) have higher than expected beef incomes. Whereas if the selection model predicted the farmer would have chosen chickens but the farmer actually chose beef cattle, that farmer would have lower beef cattle income.

Because the seasonal and quadratic terms make the climate variables difficult to interpret, we present the estimated climate response functions in Fig. 3. Fig. 3a shows how conditional net income per animal responds to temperature for each of the five

Table 2
Conditional net revenue per animal regression

	Beef cattle		Dairy cattle		Chickens		Goats		Sheep	
Variable	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic
Intercept	280	0.90	6.83	0.04	3.92	1.19	−17.1	−0.45	69.3	2.82
Temp summer	63.3	2.35	−7.98	−0.53	0.621	2.66	−5.35	−2.04	3.47	1.84
Temp summer sq	−1.15	−2.37	0.300	1.11	−0.010	−2.16	0.119	2.54	−0.041	−1.16
Temp winter	−143	−6.22	0.639	0.04	−1.29	−4.81	7.13	1.88	−10.04	−3.72
Temp winter sq	3.94	6.26	0.129	0.32	0.031	4.33	−0.196	−2.27	0.21	2.93
Prec Summer	−2.76	−3.71	−0.390	−0.78	0.007	1.08	0.033	0.56	−0.068	−1.30
Prec Summer Sq	0.009	2.74	0.002	0.84	0.000	2.32	0.000	0.77	0.000	0.92
Prec Winter	−0.882	−0.76	−0.409	−0.66	0.006	0.78	0.028	0.26	0.004	0.04
Prec Winter Sq	−0.003	−0.46	0.002	0.64	0.000	3.36	0.000	0.73	0.000	0.03
Soil Cambisols	−78.4	−0.70	92.9	1.80	−0.789	−1.10	−1.24	−0.27	−3.33	−0.90
Soil Gleysols	−428	−1.90	−516	−3.08	0.680	0.46	−18.07	−0.82	58.1	2.67
Electricity	147	4.96	−24.08	−1.35	0.376	1.87	2.13	1.01	8.18	3.94
Sale Price	−44.1	−1.67	27.2	2.39	0.419	4.00	4.82	3.34	37.7	4.76
Cattle beef—selection			−139	−2.01	3.25	3.60	−8.04	−0.54	51.2	4.75
Cattle dairy—selection	−61.2	−1.22			−1.83	−3.49	13.6	1.71	−21.8	−3.16
Goats—selection	205	0.99	380	3.39	5.65	3.55			−6.09	−0.48
Sheep—selection	313	2.47	232	2.29	−6.33	−5.14	−16.7	−1.80		
Chickens—selection	−562	−4.13	−489	−7.07			5.38	0.44	−19.2	−1.76
ADJ RSQ	0.75		0.27		0.14		0.17		0.20	
N	333		1043		888		775		842	

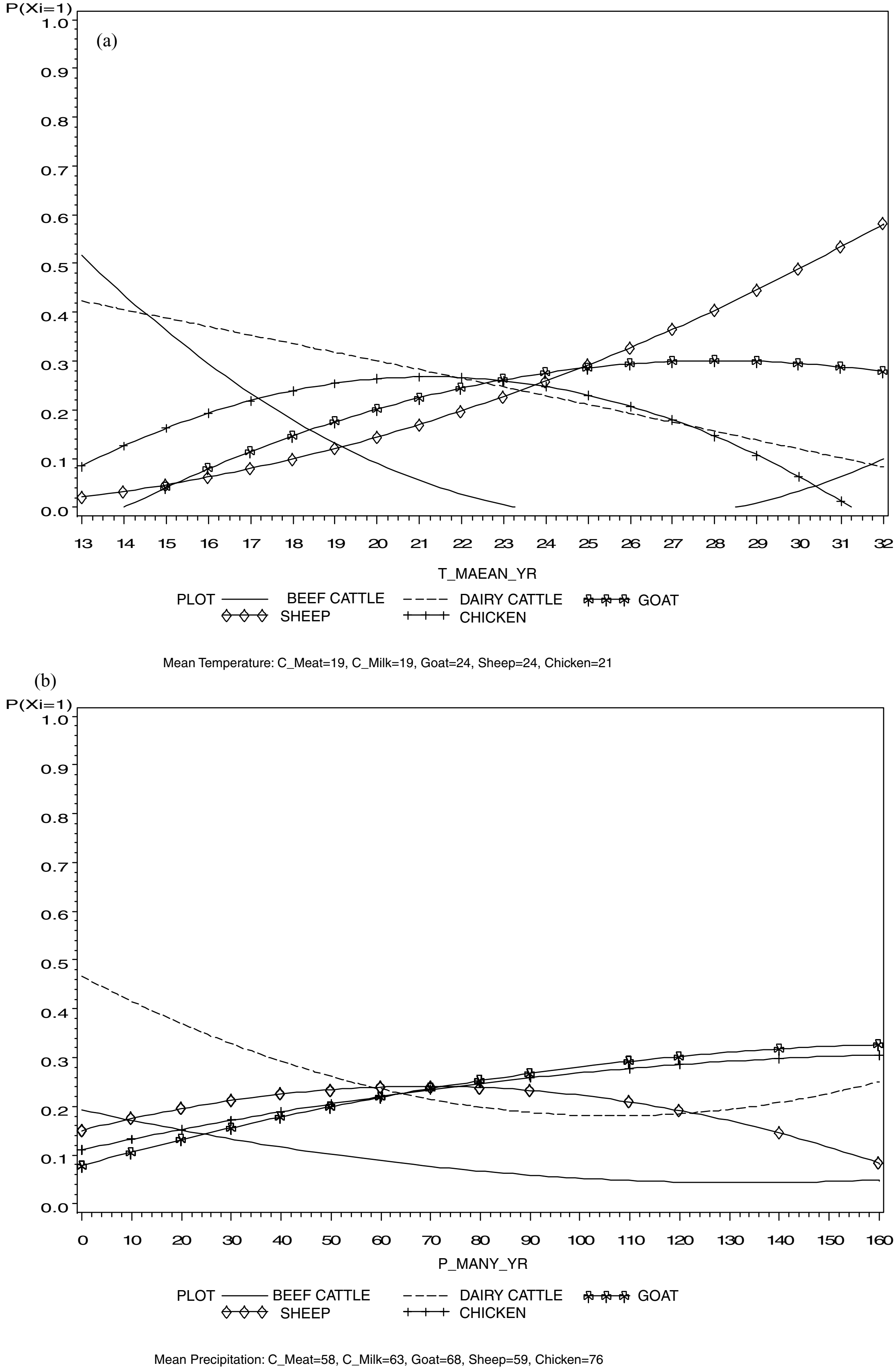

Fig. 2. (a) Estimated probability of selecting species given annual mean temperature; (b) estimated probability of selecting species given annual mean precipitation.

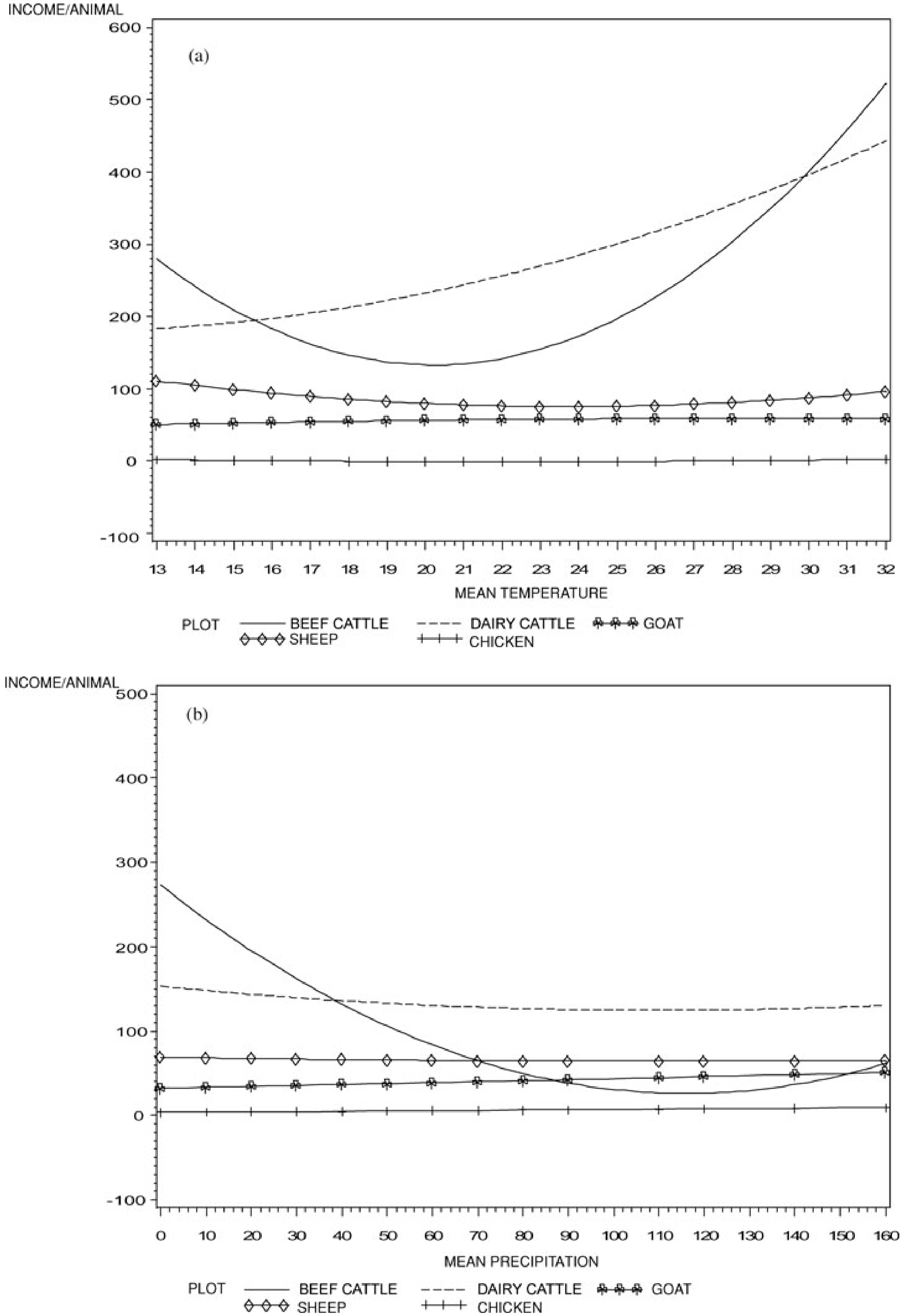

Fig. 3. (a) Estimated net revenues given annual mean temperature; (b) estimated net revenues given annual mean precipitation.

species. The conditional net income per animal is generally higher for beef cattle but it decreases rapidly as temperature rises until the temperature reaches the African mean temperature, at which point farmers stop choosing beef cattle (see Fig. 2a). Commercial beef cattle are very profitable but they are largely restricted to temperate zones in Africa. By contrast, dairy cattle net revenue increases with higher temperature. Dairy cattle operations are currently concentrated in the temperate zones in East Africa and Southern Africa, but they are more widely spread across the continent than beef cattle. The conditional net income per animal for goats, sheep, and chickens changes with temperature, but the magnitude of the change is relatively small compared to cattle. Ceteris paribus, compared to beef cattle, these smaller animals—goats, sheep, and chickens—are likely to become relatively more attractive to African farmers as temperatures rise. The figure also indicates that dairy cattle might substitute for beef cattle in higher temperatures.

Fig. 3b shows how conditional net revenue responds to precipitation. It is important in interpreting these results to recognize that increases in precipitation in Africa imply that land shifts from grassland to forest (not from unproductive to more productive pastureland). The conditional net revenue of beef cattle decreases precipitously the wetter it gets, whereas dairy cattle net revenues remain quite stable over a large range of precipitation. Sheep conditional net revenue also decreases with precipitation. The conditional net revenues of goats and chickens increase slightly.

We also estimate a third set of regressions that predict the number of animals chosen of each species. We identify this third set of regressions by the percentage of grassland in each district. Districts with more natural grassland can support more animals. As reported in Table 3, farms in districts with more grassland choose to own more beef cattle, dairy cattle, goats, and sheep per household. Farms with electricity own more animals in general but fewer sheep. Soil variables are mostly insignificant, except for the positive correlation between Gleysol soils and number of sheep. Some of the selection bias correction terms are also significant.

The number of each species of livestock is defined to be a quadratic function of summer and winter temperature and precipitation as in the two previous regressions. For each animal, some of the climate variables are significant determinants of the number of that species. Summer temperature is significant for dairy cattle, chickens, and sheep, while winter temperature is significant for goats and sheep. The number of goats and sheep has a U-shaped relationship with winter temperature. Summer precipitation is significant for beef cattle, chickens, and sheep. The response is U shaped for chickens, but hill shaped for beef cattle and sheep.

In Figs. 4a and b, we present how the estimated numbers of livestock change in response to temperature and precipitation. Fig. 4a shows that the number of beef cattle decreases sharply as temperature increases while that of dairy cattle shows a slight decrease. There are slight increases in the numbers of goats and sheep. Chickens have a U-shaped response function with respect to both temperature and precipitation, but we omit them from both figures because they are at an incompatible scale. Fig. 4b shows that the numbers of dairy cattle and goats are quite stable over a large range of precipitation, but the number of beef cattle decreases rapidly with more rainfall. The sheep increase in number as rainfall increases, despite the fact that

Table 3
Conditional number of animal regression

	Beef cattle		Dairy cattle		Chickens		Goats		Sheep	
Variable	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic	Estimate	*T*-statistic
Intercept	223	0.82	−58.05	−3.20	1, 981	1.80	20.8	0.65	14.5	0.70
Temp Summer	−12.6	−0.52	3.78	2.90	−160	−2.08	2.35	1.28	7.59	4.31
Temp Summer Sq	0.229	0.51	−0.063	−2.77	3.66	2.42	−0.037	−1.07	−0.123	−3.81
Temp Winter	−25.5	−1.09	1.21	0.83	0.046	0.00	−5.55	−1.96	−10.6	−4.34
Temp Winter Sq	0.488	0.72	−0.055	−1.43	0.143	0.06	0.142	2.12	0.224	3.65
Prec Summer	2.13	3.14	0.089	1.76	−2.42	−1.20	−0.042	−0.88	0.212	4.36
Prec Summer Sq	−0.01	−3.36	0.000	−1.89	0.022	2.85	0.000	0.71	0.000	−0.66
Prec Winter	−0.378	−0.39	0.204	3.10	1.96	0.80	0.010	0.13	0.148	1.69
Prec Winter Sq	−0.002	−0.29	−0.001	−2.45	−0.008	−0.49	0.000	−0.03	0.002	2.43
Soil Cambisols	8.87	0.09	−4.31	−0.77	251	1.05	0.806	0.21	−2.33	−0.73
Soil Gleysols	4.32	0.02	12.6	0.73	−436	−0.89	−26.8	−1.47	62.4	3.17
Electricity dummy	145	5.35	0.665	0.36	298	3.59	6.04	3.51	−1.33	−0.71
% grasslands	261	3.41	14.1	1.72	−208	−0.92	3.91	0.70	41.5	6.37
Cattle beef—selection			−4.73	−0.75	219	0.63	29.7	3.21	12.5	1.19
Cattle dairy—selection	3.71	0.08			−132	−0.70	−5.34	−0.94	−35.2	−4.98
Goats—selection	−546	−3.14	−5.45	−0.48	497	0.89			17.9	1.59
Sheep—selection	426	3.74	−16.5	−1.58	−325	−0.79	1.51	0.24		
Chickens—selection	86.1	0.72	23.3	3.44			−25.9	−2.53	16.6	1.67
ADJ RSQ	0.33		0.12		0.12		0.03		0.09	
N	381		1036		876		774		810	

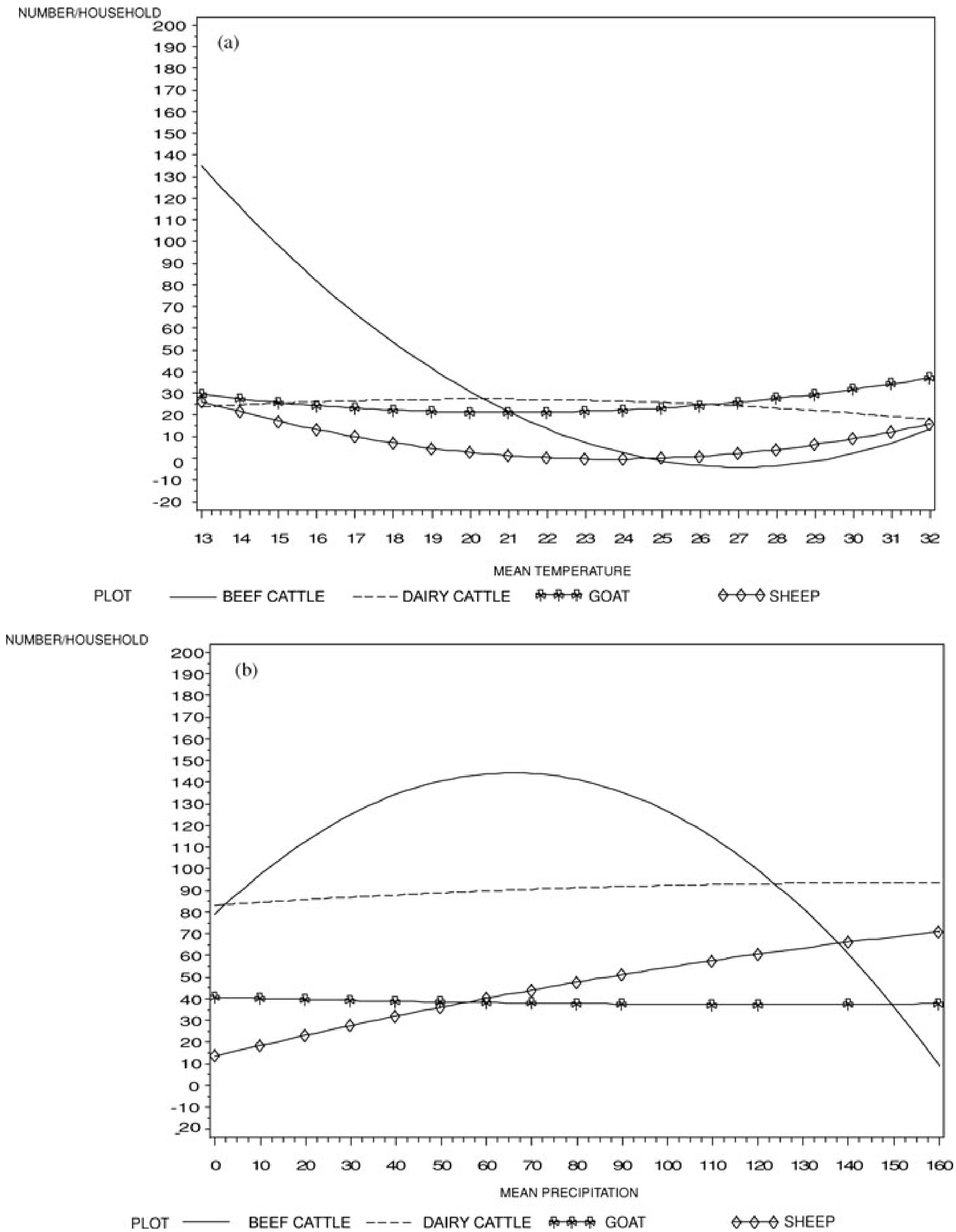

Fig. 4. (a) Estimated numbers of animals given annual mean temperature; (b) estimated numbers of animals given annual mean precipitation.

higher rainfall implies they are less frequently chosen and their net revenue declines.

Table 4 shows how all three decisions would change with a marginal change in climate. As can be seen from the top panel, as temperature rises, farmers switch away from beef cattle, dairy cattle, and chickens and toward goats and sheep. These changes are supported in the second panel of the table by the decrease in income from beef cattle in comparison to the increase in income for sheep and relatively small change in income for goats. Farmers accordingly reduce the number of

Table 4
Marginal effects of climate on outcomes

	Beef cattle	Dairy cattle	Goats	Sheep	Chickens
Probability (%)					
Baseline	9.40%	27.3%	20.8%	21.8%	22.9%
Temperature	−1.29%	−1.34%	+1.09%	+1.68%	−0.84%
Precipitation	+0.2%	−0.02%	−0.01%	−0.36%	+0.22%
Net revenue ($/head)					
Baseline	221	145	11.5	17.8	1.55
Temperature	−5.57	+11.07	−0.42	+0.13	+0.07
Precipitation	−0.72	−0.01	+0.08	−0.02	+0.03
Number (head/farm)					
Baseline	57.4	5.65	11.3	13.07	137
Temperature	−7.99	+0.01	+1.24	+0.25	+11.1
Precipitation	−0.32	+0.02	−0.01	+0.21	+3.48

Note: Temperature is measured in °C and precipitation in mm/month.

beef cattle substantially as observed in the third panel while they increase the number of goats and sheep. As rainfall increases, farmers move away from beef cattle, dairy cattle, and sheep toward goats and chickens. With the increase in rainfall, the net income of beef cattle, dairy cattle, and sheep declines, but the net income of goats and chickens increases. Although not completely consistent across the three analyses, the table clearly indicates that farmers would substitute beef cattle for goats and sheep as temperature rises and they would substitute cattle and sheep for goats and chickens as rainfall increases.

5. Climate simulations

We now simulate the consequences of climate change using the parameter estimates from the previous section. We examine a set of climate change scenarios predicted by Atmospheric Oceanic General Circulation Models (AOGCMs). The climate scenarios reflect the A2 SRES scenarios from the following three models: the Canadian Climate Center (CCC) scenario (Boer et al., 2000), Center for Climate System Research (CCSR) (Emori et al., 1999), and Parallel Climate Model (PCM) (Washington et al., 2003). The models were selected to provide a range of climate scenarios from mild (PCM) to severe (CCC). For each model, we examine country-level climate change scenarios in 2020, 2060, and 2100. For each climate scenario, we added the change in temperature predicted by each climate model to the baseline temperature in each district. We also multiplied the percentage change in precipitation predicted by each climate model by the baseline precipitation in each district or province. This gave us a new climate for every district in Africa for each model and each time period.

Table 5
African average AOGCM climate scenarios

	Current	2020	2060	2100
Temperature (°C)				
CCC	23.3	+1.6	+3.6	+6.7
CCSR	23.3	+2.0	+2.8	+4.1
PCM	23.3	+0.6	+1.6	+2.5
Rainfall (mm/month)				
CCC	79.8	−3.7%	−9.9%	−18.4%
CCSR	79.8	−7.0%	−4.0%	−22.0%
PCM	79.8	+12.5%	+1.1%	+4.3%

Table 5 summarizes the climate scenarios of the three models for the years 2020, 2060, and 2100. The models predict a broad set of scenarios consistent with the range of outcomes in the most recent IPCC (Intergovernmental Panel on Climate Change) report (Houghton et al., 2001; IPCC, 2007). In 2100, PCM predicts a 2°C increase, CCSR predicts a 4°C increase, and CCC predicts a 6°C increase in temperature in Africa. Rainfall predictions are noisier: PCM predicts an average 10% increase, CCC predicts a 10% decrease, while CCSR predicts a 30% average decrease of rainfall in Africa. In addition to the mean rainfall in Africa varying substantially across the scenarios, there is also substantial variation in rainfall across countries within each scenario.

The three climate models predict temperatures to increase steadily until 2100 although at different rates. Precipitation predictions, however, vary across time: CCC predicts a declining trend; CCSR predicts an initial decrease, and then increase, and decrease again; PCM predicts an initial increase, and then decrease, and increase again.

We used the parameters from our estimated models in the previous section to simulate the impacts of climate change on the expected revenue of livestock management under various scenarios. Table 6 shows the changes in the probabilities of choosing a particular species for each climate scenario. CCC scenario predicts farmers to shift away from beef cattle, dairy cattle, and chickens to goats and sheep by 2020. Under the wet PCM scenario, sheep ownership also declines. Under the dry CCSR scenario, beef cattle are chosen less often, but to a lesser degree. These results are consistent with our earlier response

Table 6
Predicted change in the probability of selecting each animal from AOGCM climate scenarios

	Beef cattle	Dairy cattle	Goats	Sheep	Chickens
Baseline probability	9.40%	27.3%	20.8%	21.8%	22.9%
2020					
CCC	−1.48%	−3.09%	+2.48%	+3.10%	−1.89%
CCSR	−0.91%	−3.94%	+2.43%	+2.81%	−1.06%
PCM	−2.73%	−5.17%	+10.21%	−4.10%	−1.93%
2060					
CCC	−2.15%	−6.59%	+10.4%	−2.49%	−2.82%
CCSR	−3.47%	3.10%	+0.07%	+1.28%	−3.44%
PCM	−2.40%	−3.35%	−1.14%	+9.59%	−5.01%
2100					
CCC	−0.83%	−6.53%	−3.34%	+15.9%	−9.94%
CCSR	−0.41%	−6.23%	+6.45%	+3.18%	−4.10%
PCM	−1.83%	−7.35%	+10.7%	−2.19%	−4.55%

Table 7
Predicted change in net income per animal from AOGCM climate scenarios (US$/animal)

	Beef cattle	Dairy cattle	Goats	Sheep	Chickens
Baseline	224	150.1	11.1	16.7	1.60
2020					
CCC	+6.71	+19.9	−1.45	−1.06	+0.26
CCSR	−0.89	+19.9	−1.48	−1.12	+0.45
PCM	−82.7	+29.4	+3.75	−4.10	+3.02
2060					
CCC	−78.8	+33.8	+2.37	−3.30	+3.08
CCSR	−44.6	+12.5	−1.92	−3.51	+0.84
PCM	+30.8	+32.8	−5.07	+0.17	+0.70
2100					
CCC	+100.6	+68.1	−7.84	+1.69	+1.82
CCSR	−24.9	+49.8	+1.13	+0.75	+1.85
PCM	−66.8	+44.8	+1.90	−4.12	+3.46

Table 8
Predicted change in numbers of each animal per farm from AOGCM climate scenarios (animals/farm)

	Beef cattle	Dairy cattle	Goats	Sheep	Chickens
Baseline	58.3	5.50	11.7	13.6	140.9
2020					
CCC	−12.9	+0.39	+3.94	+1.68	+41.8
CCSR	−9.91	+0.95	+4.13	+3.30	+8.86
PCM	−24.8	−0.46	+3.99	+31.1	+122.7
2060					
CCC	−22.9	−0.34	+6.34	+29.8	+108
CCSR	−19.2	−1.07	+4.73	+7.13	+27.9
PCM	−19.8	−0.39	+12.4	+2.61	+60.7
2100					
CCC	−27.6	−1.39	+24.8	+9.97	+204
CCSR	−37.2	+1.18	+8.54	+14.1	+207
PCM	−30.4	−0.59	+8.95	+34.1	+178

functions of species choices in Figs. 2a and b. This general trend also continues until 2100.

We show the changes in the conditional net incomes per animal in Table 7. By 2100, the net income from beef cattle will decrease over the next century by 30% with the PCM scenario, by 10% according to the CCSR scenario, but increase by 50% according to the CCC scenario. Net incomes for dairy cattle increase by 30–50% by the year 2100. Net incomes for sheep increase with the CCC and CCSR scenarios, but decrease with the PCM scenario. On the contrary, net incomes for goats increase according to CCSR and PCM scenarios, but decrease with the CCC scenario. Net incomes for chickens increase especially under the wet PCM scenario in 2100.

Table 8 calculates the changes in the number of animals of each species for each climate scenario. These results are consistent with the previous two tables on probabilities and net incomes indicating that beef cattle will decline substantially while goats, sheep, and chickens will increase over the coming century. Across the models, the number of beef cattle is predicted to decrease by an average of 15 per farm in 2020, 20 per farm in 2060, and 33 per farm in 2100. The number of dairy cattle is predicted to remain quite stable over the next 100 years. Goats increase in number by 4 in 2020, by 7 in 2060, and by 13 on average in 2100. The numbers of sheep and chickens also are expected to increase.

Combining the results from Tables 6, 7, and 8, the expected change in net income is shown in Table 9 for each AOGCM scenario. The current average income from livestock management is around $900. For all the scenarios, the expected income from livestock farms is expected to drop substantially by 2020, by between 15 and 20%. In the CCC scenario, the loss from livestock sector declines to 10% by 2060 and turns into a large gain by 2100. With the CCSR scenario, the damages increase to 25% in 2060 with more precipitation but then shrink again by 2100. With the PCM scenario, there is a 15% loss of income by 2020, but this loss is offset completely by 2060, and turns into a gain by 2100.

African farmers are expected to lose income initially because they must switch away from beef cattle to animals that provide lower returns (thus lowering the net income per animal) and reducing the number of valuable animals. These net results are consistent with the traditional Ricardian analysis of the

Table 9
Predicted change in expected income from AOGCM climate scenarios (US$)

	Mean (US$/farm)	% Change	Total (billions US$)	Bootstrap lower 95%	Bootstrap upper 95%
Expected income	882		60		
2020					
CCC	−162	−18.4%	−11.05	−220.1	−104
CCSR	−176	−19.9%	−11.9	−236	−115
PCM	−137	−15.5%	−9.33	−214	−60
2060					
CCC	−101	−11.4%	−6.88	−178	−23.9
CCSR	−220.1	−24.9%	−14.9	−292	−148
PCM	+5.1	+0.58%	+0.35	−70.8	+81.1
2100					
CCC	+1488	+168%	+101.2	+1343	+1633
CCSR	−71.3	−8.08%	−4.85	−143	+0.59
PCM	55.2	6.26%	+3.76	−24.8	+135

same data (Seo et al., 2007). However, farmers will be able to substitute species, reducing this initial damage over time. The 95% confidence interval was calculated for all of these estimates using 200 bootstrap runs. The estimated damages are significantly different from zero for most of the AOGCM scenarios in 2020, 2060, and 2100 except for the PCM scenarios in 2060 and 2100.

Table 9 also extends the analysis from the sample to all farms in Africa. This leads to an estimate of the aggregate livestock impact across Africa. The results suggest that the damage will vary from a loss of \$9 to \$12 billion in livestock income in 2020, from zero to a \$15 billion loss in 2060, and finally from a loss of \$5 billion to a gain of \$100 billion in 2100. In the long run, climate change will be beneficial to the livestock sector in Africa and this will offset some of the expected losses to crops (Kurukulasuriya et al., 2006).

6. Conclusion

This article uses a structural equation model to capture the endogenous choices made by farmers and their resulting expected income. The model assumes that farmers choose the profit-maximizing level of inputs for each animal, the species that provides the highest net revenue, and the number of animals of that species. The article tests whether these decisions are influenced by climate. The resulting model gives insights into how farmers might adapt to climate change.

The model is applied to 5,000 livestock farmers in Africa. The multinomial choice model reveals that the probability of selecting beef cattle, dairy cattle, and chickens diminish sharply in warmer places. This is completely consistent with the observation that commercial cattle operations are currently located only in temperate locations across Africa, such as South Africa and Kenya. Furthermore, the model predicts that numbers of goats and sheep will increase with warming. This again is consistent with observations of where goats and sheep are currently located, in relatively hot locations such as Burkina Faso, Niger, and Senegal. The model also reveals that beef cattle and sheep are more common in dryer areas, whereas goats and chickens are more common in wetter locations.

The conditional net revenue analysis supports the multinomial choice results in general. Net revenue of beef cattle is lower in warmer places, but net revenue of sheep is higher in warmer places. In a wetter place, net revenue from goats and chickens is higher, but sheep net revenue is lower. Consequently, farmers move away from beef cattle to goats and sheep in warmer places. Farmers shift from cattle and sheep to goats and chickens in wetter places and the reverse in dryer places.

Finally, the predicted number of animals of each species is also consistent with the results from the multinomial logit choice and conditional net revenue analysis. The number of beef cattle declines rapidly with warming while the number of dairy cattle changes little. By contrast, the number of goats, sheep, and chickens increases. With a precipitation increase (decrease), the number of beef cattle declines (increase) while the number of chickens increases (falls). As the net profitability of livestock falls, farmers will reduce their investments in that livestock and reduce their herds. This is especially evident with beef cattle and warmer temperatures.

There has been very little quantitative research on animal husbandry in Africa so there are few empirical studies with which to compare these results. A standard Ricardian analysis was done by Seo et al. (2007), using the same data. The results of the standard Ricardian model are not exactly the same but are consistent with the results in this article. That is, the Ricardian analysis predicted that net revenues of large commercial farms will fall with either rising temperature or rising rainfall levels, but those of small household farms will increase with warming due to their reliance on goats and sheep.

All the AOGCM predictions suggest that the expected profit from African livestock management will fall as early as 2020. Most of this effect is from the falling profitability of large beef cattle operations. Even small changes in temperature will be sufficient to have a relatively large effect on beef cattle operations. Additional warming will still be harmful, but farmers will be able to make necessary substitutions to avoid further damages, thereby lessening the magnitude of damage. Large farms dependent on beef cattle will be especially hard hit. In contrast, small farms that switch to sheep or goats may not be as vulnerable to higher temperatures compared with large farms that cannot make this switch.

Precipitation also plays an important role in the AOGCM results. Scenarios with more precipitation, for example the CCSR 2060 scenario, are more harmful. Because pastures and ecosystems in general are more productive with more rain, this result may seem counterintuitive. However, in Africa, increased precipitation may increase animal diseases such as Nagana, East Coast Fever, and Rift Valley Fever that are quite significant for livestock (Ford and Katondo 1977; University of Georgia, 2007). Perhaps more importantly, more rain shifts savanna or grasslands into forest ecosystems (Sankaran et al., 2005). These grasslands are more productive for sheep, dairy cattle, and beef cattle. Reductions in precipitation from large to moderate levels appear to be beneficial to livestock. As long as there is sufficient precipitation to support grasslands, livestock will gain.

This analysis reveals one way that farmers will be able to adapt to climate change. It suggests that small farmers will switch species and move away from beef cattle, dairy cattle, and chickens toward goats and sheep. Small farmers will be able to make these changes without much change in expected income. However, climate change is predicted to reduce the net incomes of large farms considerably. African policy makers must be careful to encourage private adaptation during this period of change. There may be nothing that can be done to sustain the large cattle operations that depend on current climate. Providing subsidies or other enticements for such operations to continue once climate changes occur would only compound the situation. Instead, governments should encourage farmers to change the composition of animals on their farms as needed. That is, they should inform farmers about how other livestock owners have coped with higher temperatures and share indigenous knowledge. Governments should anticipate that farmers will make changes on their lands and do whatever is needed to facilitate these changes.

In interpreting these results, there are several caveats that should be kept in mind. First, this analysis does not include the effect of global warming on prices. We assumed global market prices of livestock are relatively stable over the century. If instead there are large changes in livestock prices, these results will overestimate the welfare effects of climate change. Second, we assumed adaptations can take place as needed. For example, farmers can switch across types of livestock as temperature increases and rainfall decreases. However, this may not be the case if the adjustment requires a heavy capital investment or substantial learning. Third, we assumed that in forecasting climate change impacts, the only thing that changes in the future is climate. Many things, however, will change over the century, including population, technologies, institutional conditions, and reliance on agriculture and livestock. Fourth, we assumed that ecosystems will change quickly as climate changes. This may not be the case as many forest ecosystems that will eventually shift to another ecosystem may survive well into the future. Fifth, the analysis did not examine climate variation or extreme events. Although it is not clear whether climate variance will change in the future (IPCC, 2007), any change in climate variance is likely to have a profound effect on African livestock. Lastly, the survey collected only limited data on the cost of raising livestock. The study did not have a complete account of all the costs of raising livestock. Future studies should address these issues to provide more accurate measures of climate change impacts.

The overall conclusions of the analysis suggest that there will be damages from global warming to African livestock in the next 20 years of between \$9 and \$12 billion. Damages in midcentury will depend on precipitation patterns. In the long run, global warming will likely be beneficial to the livestock sector in Africa and this will help offset some of the expected losses to African crops (Kurukulasuriya et al., 2006).

Appendix 1: Description of the variables

Variables	Description
Temperature summer	Average of May, June, and July temperature in the northern hemisphere obtained from the U.S. Defense Ministry satellites for the period of 1988–2004. Average of November, December, and January temperature in the southern hemisphere.
Temperature summer sq	$(\text{Temperature summer})^2$
Precipitation summer	Average of May, June, and July Precipitation in the northern hemisphere obtained from the U.S. Defense Ministry satellites for the period of 1988–2004. Average of November, December, and January precipitation in the southern hemisphere.
Precipitation summer sq	$(\text{Precipitation summer})^2$
Temperature winter	Average of November, December, and January temperature in the northern hemisphere obtained from the U.S. Defense Ministry satellites for the period of 1988–2004. Average of May, June, and July temperature in the southern hemisphere.
Temperature winter sq	$(\text{Temperature winter})^2$
Precipitation winter	Average of November, December, and January precipitation in the northern hemisphere obtained from the U.S. Defense Ministry satellites for the period of 1988–2004. Average of May, June, and July precipitation in the southern hemisphere.
Precipitation winter sq	$(\text{Precipitation winter})^2$
Soil Cambisols	Parent materials are medium- and fine-textured materials derived from a wide range of rocks, mostly in colluvial, alluvial, or aeolian deposits. Cambisols are characterized by slight or moderate weathering of parent material and by absence of appreciable quantities of illuviated clay, organic matter, aluminium, and/or iron compounds. This soil is found at level to mountainous terrain in all climates and under a wide range of vegetation types.
Soil Gleysols	Wetland soils that, unless drained, are saturated with groundwater for long enough periods to develop a characteristic "gleyic colour pattern"
Electricity	A dummy variable for electricity
Beef cattle price	Price of 1 beef cattle
Milk price	Price of 1 liter of milk
Goats price	Price of 1 goat
Sheep price	Price of 1 sheep
Chickens price	Price of 1 chicken
Sale price	Sale prices of the corresponding livestock
% grasslands	Percentage of grassland within a district
P_k	Probability that species k is chosen
Net revenue per species k	Net revenue earned from species k divided by the number of the species
Number of species k	Number of species k at the farm
Expected net revenue	Summation over all species of P_k^* Net revenue per species k^* Number of species k

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