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The impact of climate change on crop production in Ghana: A Structural Ricardian analysis

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Abstract

We apply a Structural Ricardian Model (SRM) to farm-level data from Ghana in order to estimate the impact of climate change on crop production. The SRM explicitly incorporates changes in farmers' crop selection in response to variation in climate, a feature lacking in many existing models of climate change response in Africa. Two other novel features of our model are an estimate of the response of agricultural profits to differences in land tenure, and a comprehensive investigation of the appropriate functional form with which to model farmers' responses. This final feature turns out to be important, since estimates of the effect of climate change turn out to be sensitive to the choice of functional form.

JEL classification: O13; O55; Q12; Q54

Keywords: Structural Ricardian Model; climate change; Ghana

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1. Introduction

Many developing countries are especially sensitive to climate change because they are located in the tropics, with temperatures that already compromise agricultural production (Da Cunha *et al*., 2015; Kurukulasuriya *et al*., 2006; Mendelsohn *et al*., 2006), and because they have limited access to the human and physical capital that might mitigate its effects (Di Falco, 2014). These challenges are often compounded by a lack of access to new technology and to developed markets (Di Falco, 2014; Kurukulasuriya *et al*., 2006). Ghana is one example of a country facing these challenges. Less than 1% of its land is under irrigation and the vast majority of its farmers rely entirely on rainfall (MoFA, 2010; 2014; World Bank, 2010).

In this paper we present estimates of the effect of climate change on Ghana based on the application of a Structural Ricardian Model (SRM) to a large microeconomic dataset. The first stage in the model is designed to estimate farmers' crop choices – a feature that is absent from many other estimates of climate change effects in developing countries – while the second stage is designed to estimate farm revenue conditional on these choices. The model is then used to simulate the impact of climate change under various climate scenarios. Our model incorporates two other innovative features absent from many applications of the SRM. Firstly, we explicitly allow crop choice to depend on the form of land tenure, which is known to affect agricultural production through its impact on investment decisions and access to credit (Fenske, 2011). Secondly, we apply the model in a way that allows for a variety of alternative functional forms. Our results turn out to be highly sensitive to the choice of functional form, and we find that inappropriate functional form restrictions can lead to misleading results. In this respect our findings are in line with the Italian study of De Salvo *et al*. (2013).[1]

[1] Other authors, for example Fezzi and Bateman (2013), have found results that are not sensitive to

2. An overview of the SRM

In a traditional Ricardian model of farm productivity, farmers are assumed to allocate their land to different crops so as to maximize profit, and therefore land values reflect the present discounted value of future farm revenue (Mendelsohn *et al*., 1994; 1996). This model has been criticised for failing to pay sufficient attention to the factors that drive crop selection (Elbehri and Burfisher, 2015; Kurukulasuriya and Mendelsohn, 2008; Seo and Mendelsohn, 2008), and the SRM addresses this criticism by incorporating an explicit model of the farmer's choice of crops. In our version of the model, assume that the desirability of crop *j* on plot *i* is given by:

$$y_{ij}^{*} = \beta_j x_i + v_{ij} \tag{1}$$

Here, x_i stands for a vector of farm characteristics and β_j stands for a vector of parameters to be estimated. If the error term v_i is drawn from a Gumbel Distribution and if the farmer of plot *i* chooses the most desirable crop, then the probability that crop *j* will be chosen out of *J* alternatives (P_{ij}) is given by the following equation (McFadden, 1973):[2]

$$P_{ij} = \frac{\exp(\beta_j x_i)}{\sum_{k=0}^{k=J} \exp(\beta_k x_i)} \tag{2}$$

Suppose further that the annual net revenue per hectare from crop *j* (φ_{ij}) is given by the following function:

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functional form restrictions, but our results add weight to the argument that such restrictions should not be assumed *a priori*.

[2] This specification of the first-stage regression equation assumes the Independence of Irrelevant Alternatives (IIA). Bourguignon *et al*. (2007) find that violation of the IIA assumption does not impair the consistency of the estimates of the second-stage regression equation, i.e. equation (4) below. Nevertheless, we tested for violation of the IIA assumption using the method of Small and Hsiao (1985). Using this test, we cannot reject the IIA assumption at conventional confidence levels.

$$\frac{\varphi_{ij}{}^{(\theta)}-1}{\theta} = \alpha_j z_i + w_{ij} \tag{3}$$

Here, z_i stands for a vector of farm characteristics (excluding at least one of the x_i variables), α_j stands for another vector of parameters to be estimated, and w_{ij} stands for a normally distributed error term. The left hand side of equation (3) is a Box-Cox transformation incorporating the parameter θ (Box and Cox, 1964). Direct estimation of this equation is likely to suffer from selection bias but, having fitted equation (2) to the data using a multinomial logit model, the bias can be corrected by fitting the following equation (Dubin and McFadden, 1984; Bourguignon et al., 2007; Seo and Mendelsohn, 2008):

$$\frac{\varphi_{ij}{}^{(\theta)}-1}{\theta} = \alpha_j z_i + \sigma \frac{\sqrt{6}}{\pi} \sum_{k \neq j} r_{kj} \cdot \left(\frac{P_{ik} ln(P_{ik})}{1-P_{ik}} + ln(P_{ij}) \right) + w_{ij} \tag{4}$$

Here, $r_{kj} = corr(w_{ij}, v_{ik})$ and σ is a variance parameter; $\sigma \cdot r_{kj}$ can be estimated directly.

See De Salvo et al. (2013) for a previous SRM application of the Box-Cox transformation. This transformation allows the equation for net revenue to take a range of alternative functional forms, encompassing equations in levels (e.g. Coster and Adeoti, 2015; Fleischer et al., 2008; Kurukulasuriya and Ajwad, 2007; Mendelsohn *et al.*, 1996; Seo and Mendelsohn, 2008) as well as inverse and semi-logarithmic functions (e.g. Chatzopoulos and Lippert, 2015; Fezzi and Bateman, 2013). Another attractive feature of Box-Cox transformation is its ability to compensate for heteroscedasticity (Blaylock *et al.*, 1980). In the special case of $\theta = 1$ we have a model in levels, in the case of $\theta = 0$ we have a logarithmic model, and in the case of $\theta = -1$ we have an inverse transformation (Box and Cox, 1964).

In our application of the model, the x_i variables in equations (1-2) comprise the following features:

• $temp_i$: the mean temperature observed on plot i, and $(temp_i)^2$.

• $precip_i$: mean precipitation observed on plot i, and $(precip_i)^2$.

• $tenure_i$: the form of land tenure applicable to plot i.

• $soil_i$: a measure of soil quality on plot i.

• age_i: the age in years of the head of the household farming plot i.

• $male_i = 1$ if the head of the household farming plot i is male; otherwise $male_i = 0$.

• $non\text{-}farm\text{-}income_i$: the gross non-farm income of the household farming plot i.

The z_i variables in equations (3-4) comprise all of these features except $non\text{-}farm\text{-}income_i$. Non-farm income allows the household to bear periods with no income from crops, and so to plant crops which take a long time to grow; in Ghana this is particularly relevant to plantain, which is a perennial crop. It is also likely that non-farm income will be positively associated with the cultivation of maize, which is especially reliant on costly inputs such as inorganic fertilizers, pesticides and weedicides (Coster and Adeoti, 2015; Kanton *et al*., 2016). However, non-farm income should not affect the productivity of the land once the crop has been planted.[3]

3. Data

The data for φ_{ij}, $tenure_i$, age_i, $male_i$, and $non\text{-}farm\text{-}income_i$ are taken from the sixth round of the Ghana Living Standards Survey (GLSS), published by the Ghana Statistical Service. This survey was implemented between 18 October 2012 and 17 October 2013 (Ghana Statistical Service, 2014). The results below are based on observations for the 6,321 farming households in the sample. For the dependent variables φ_{ij}, net revenue is measured as the total US Dollar

[3] It turns out that the correlation between *temp* and $(temp)^2$ makes estimates of non-linear temperature effects in second-stage model of revenue very imprecise, so in results reported below $(temp)^2$ is omitted at the second stage. However, our *a priori* identification restriction is on *non-farm-income*.

value of crop j less production costs, as reported by the head of the household farming plot i.[4] Our analysis is confined to the most important income-generating crops in Ghana: maize (*Zea mays*), rice (*Oryza spp*), cassava (*Manihot esculenta*), plantain (*Musa spp*), groundnuts (*Arachis hypogaea*), and millet (*Pennisetum glaucum*). $Tenure_i$ is measured as a binary variable indicating whether the land is communal ($tenure_i = 0$) or private ($tenure_i = 1$). We define private land as land that the household has procured individually, has long-term rights to, and can use for any purpose. Communal land belongs to the extended family or to the community, and the household has no property rights over this land, which accounts for about 80% of all farmland in Ghana (Pande and Udry, 2005). Farmers with private land are usually able to recoup the investments they make, but investment in communal land carries no such guarantee. We anticipate that farmers will be more likely to invest in their land if it is owned privately (Kurukulasuriya and Ajwad, 2007), increasing net revenue. We also anticipate that net revenue will be higher if the household head is male. Households with female heads may have less access to resources, or face discrimination in the market place, or have fewer men to work in the fields when the women have childcare responsibilities (Coster and Adeoti, 2015; Kurukulasuriya and Ajwad, 2007). The effect of age on revenue could be positive, if it associated with greater experience (Coster and Adeoti, 2015; Fleischer et al., 2008), or negative, if households with older heads are less physically capable.

The climate variables ($temp_i$, $precip_i$) are constructed from historical weather station data for the period 1973-2011 (National Oceanic and Atmospheric Administration, 2015). We match the GLSS data to the climate data at a spatial resolution of one degree. $Temp_i$ is defined as the mean recorded temperature over the period (in degrees centigrade) and $precip_i$

[4] A plot is defined as all land allocated to a particular crop by a single household.

is defined as mean recorded precipitation (in millimetres).[5,6] The variable $soil_i$ is constructed from data provided by the Soil Research Institute of Ghana's Council for Scientific and Industrial Research (CSIR-SRI). $Soil_i$ = 1 indicates relatively fertile soil (soil types I-IV as defined by the CSIR-SRI) while $soil_i$ = 0 indicates relatively infertile soil (types V-VI).[7]

Table 1 reports descriptive statistics for the variables in our model disaggregated by crop. The table shows some strong associations between crop type and farm characteristics, although it is important to note that these are unconditional associations. Rice, plantain and cassava tend to be cultivated in relatively high-precipitation areas while millet and groundnuts are cultivated in relatively low-precipitation areas; maize represents an intermediate case. Plantain, cassava and maize are also associated with relatively fertile soil, while groundnuts and millet are associated with relatively infertile soil; rice represents an intermediate case. There is no substantial variation in the mean temperature associated with the different crops. Average net revenues from rice and groundnut cultivation are much higher than for other crops. Plantain cultivation is associated with relatively high non-farm income and millet cultivation with relatively low non-farm income. For all crops, however, there is substantial variation across households in both the net revenue from the crop and the

[5] Alternatively, we might include seasonal climate variables, for example mean temperature and precipitation for each month or for each quarter of the year. However, the seasonal measures in our dataset are highly collinear and have no significant explanatory power in our model.

[6] A model incorporating spatially interpolated climate variables may suffer from an errors-in-variables problem (Chatzopoulos and Lippert, 2015). In order to explore this potential problem, we fitted a model in which latitude, longitude, visibility, maximum sustained wind speed and sea level pressure were used as instruments for *temp* and *precip*. Using the Wooldridge Score Test (Wooldridge, 1995), it was not possible to reject the null hypothesis that *temp* and *precip* are exogenous at conventional confidence levels.

[7] Soil type I is non-gravelly and medium to moderately heavy textured. Soil type II is medium to moderately heavy textured but gravelly. Soil type III, which is mostly alluvial, may contain gravelly and moderately shallow soil or heavy plastic clay. Soil type IV is shallow and imperfectly drained. Soil type V comprises poorly drained soils or terraced-derived soils containing pebbles. Soil type VI is very saline. Adding indicator variables for individual soil types does not produce statistically significant coefficients.

non-farm income of the households cultivating it. There is a relatively high proportion of households with female heads farming the perennial crops, cassava and plantain, and these crops are also associated with a relatively high incidence of private land tenure. There is little variation in the average age of the household head across different types of crop.

4. Modelling the impact of climate change on crop production

4.1. The selection equation

Individual parameter estimates from the multinomial crop selection model in equation (2) are presented in Appendix 1. A Wald χ^2 test shows that the explanatory variables are jointly significant at the 1% level, while the count R^2 statistic indicates that the regressors explain over 50% of the variation in crop selection. Table 2 presents the corresponding marginal effects for all variables except *temp* and *precip*, evaluated at the mean shares of each crop, along with heteroscedasticity-robust standard errors. Table 2 shows marginal effects that are somewhat different from the unconditional associations in Table 1, which reflects significant correlations across the different explanatory variables and suggests that great care should be taken when interpreting the unconditional associations.

Table 2 shows that higher soil quality is associated with a significantly greater probability of cultivating maize and cassava (and plantain, although this effect is relatively small), while the other crops – groundnuts, rice and millet – are associated with low-quality soils. It is already known that maize requires especially fertile soil (Coster and Adeoti, 2015; Kanton *et al*., 2016), and that groundnuts are particularly suitable for low-quality land because of their ability to fix atmospheric nitrogen (Kombiok *et al*., 2012). Perennial crops such as cassava and plantain may be allocated to more fertile soils in order to minimize soil improvement costs. The table also shows that private land tenure is associated with a significant rise in the probability of maize cultivation and a significant fall in the probability of groundnut, millet and plantain cultivation. One possible explanation for these effects is that efficient maize cultivation is associated with long-term investments that are larger, on average, than for other crops, and that private land tenure incentivizes such investments. However, differences in capital investments across crops are not well documented, so this is a topic for future research.

Age and sex of the household head also have significant effects on crop selection. Older farmers are more likely to select cassava but less likely to select groundnuts and rice. One possible explanation, which requires further research, is that groundnuts and rice are more likely to be sold at market, while cassava is more likely to be consumed by the household, and that food makes up a greater share of the total consumption of households with older heads. Households with female heads are more likely to cultivate the perennial crops (cassava and plantain) and less likely to cultivate millet and maize; these effects are statistically significant. Cassava and plantain require some post-harvest processing in order to preserve them, and these tasks are often undertaken by women (African Development Fund, 2008). Moreover, cassava and plantain are harvestable throughout the year (Dziedzoave *et al*., 2006), so a household specializing in these crops will not have to compete with other farmers for tractors and casual labour at the beginning of the season. This makes them particularly suitable for households with less bargaining power in the local community.

As anticipated, higher non-farm income is associated with a greater probability of maize and plantain cultivation. It is also associated with a smaller probability of millet cultivation; these effects are statistically significant.

The inclusion of quadratic terms in *temp* and *precip* allows the effect of these variables to be non-monotonic, so Figures 1-2 show the predicted probability of the selection of different crops at different temperature and precipitation levels, along with the corresponding 95% confidence interval. These effects are estimated at the mean values of the other regressors. Figure 1 shows that at moderate temperatures (below 26.5 degrees centigrade) around 60% of the land is under maize cultivation and almost no land is under millet cultivation. Above 26.5 degrees there is substantial switching from maize to millet, and at 28 degrees almost all of the land is under millet cultivation. See Aidoo et al. (2016) for a discussion of the characteristics of millet which make is especially tolerant of high temperatures. Rises in temperature are associated with a gradual decline in the proportion of land devoted to cassava and (to a lesser extent) plantain: at 25 degrees these crops together account for about 40% of the land under cultivation, this figure dropping to almost zero at 28 degrees. Groundnuts account for about 20% of land under cultivation at mid-range temperatures (25.5-26.5 degrees), but a very small proportion outside this range. The cultivation of rice is relatively invariant to temperature.

Figure 2 shows that there are several non-monotonic precipitation effects. The cultivation of the annual crops (maize, groundnuts, rice and millet) is most frequent at intermediate precipitation levels. Maize cultivation reaches a peak at 1200mm of rainfall, millet at 1400mm, groundnuts at 1500mm, and rice at 1700mm. In extremely dry conditions (below 1100mm), only 40% of the land is allocated to maize and almost no land is allocated to the other annual crops. In extremely wet conditions (above 1800mm), almost no land is allocated to any of the annual crops. At extreme levels of precipitation the dominant crop is cassava. Cassava has an extensive root system that protects it from drought and is robust enough to withstand high rainfall (Dziedzoave *et al*., 2006).

4.2. The revenue equation

Table 3 presents estimates of the parameters in equation (4). Estimates of the θ parameter for each crop range from 0.07 to 0.18: these numbers are significantly greater than zero but significantly less than one ($p < 0.05$ in all cases), so we can reject the linear, inverse, and log-linear specifications of the SRM. For each crop, the first column in the table reports the parameter estimates in the unrestricted model (with a fitted value of θ), while subsequent columns reports parameter estimates from a semi-log-linear model (imposing $\theta = 0$) and from a linear model (imposing $\theta = 1$). Here we concentrate mainly on the results in the first column, while the other columns show how the results differ if a specific functional form is assumed. The Box-Cox transformation is non-linear, so the coefficients cannot be compared directly across the columns, and further results comparing individual marginal effects in the different models are available on request. The rest of this section discusses the sign and statistical significance of different effects, leaving the discussion of the size of the effects of climate change in the different models to the next section.

Before discussing estimates of the α coefficients in Table 3, we note that several of the selection effects (r_{kj}) are significant at the 5% level. Restricting attention to the first column for each crop (i.e. our preferred model), all but one of these significant effects is negative: that is, a plot which is predicted to be used for crop *k* but is instead used for crop *j* can be expected to generate less revenue from this crop than otherwise. One interpretation of these effects is that the average household is making reasonably efficient crop selection decisions. These decisions are characterized in Table 2, and households which deviate from the average are less efficient. The one exception is that maize plots which are predicted to be used for plantain generate higher revenue than otherwise. However, this represents a single anomalous coefficient out of 25.

In interpreting the effect of temperature in equation (4), it is important to remember that the different crops are typically grown in different climatic ranges. Of the three crops showing a significant negative effect of temperature on revenue, one (millet) is the crop which predominates at very high temperatures, while the other two (plantain and rice) have a probability of selection that is relatively invariant to temperature. The crops which show the largest reductions in the probability of selection at very high temperatures in Figure 1 (cassava, groundnuts and maize) show positive temperature effects in Table 3,[8] although in the Box-Cox model these effects are statistically insignificant. One interpretation of the Table 3 results is that when temperatures are high enough to threaten the yields of cassava, groundnuts or maize, farmers immediately substitute into millet, which is the most heat-tolerant crop. One might ask whether farmers substitute too readily into millet. The absence of positive millet selection effects ($r_{millet j}$) in Table 3 suggests that farmers are *generally* making the right decisions about when to grow millet; however, the absence of negative temperature effects for cassava, groundnuts and maize suggests further research into the relative returns to millet production at the critical temperature margin, around 27 degrees.[9]

The two crops for which there is an effect of land tenure on revenue that is significant at the 5% level are cassava and maize. This is consistent with the Table 2 results: private land tenure is also associated with a greater probability of maize and cassava cultivation, although the second effect is not statistically significant. For all crops except plantain, the sex of the household head has a significant effect on revenue. *Ceteris paribus*, households with female heads are earning revenues that are about half as large as those of other households. Similar results appear in Coster and Adeoti (2015) and in Kurukulasuriya and Ajwad (2007), who suggest that this effect can be explained by differential access to productive resources and discrimination in the market place. The one crop for which there is a significant effect of the age of the household head on revenue is maize. The effect is negative, as in Ajetomobi *et al*. (2010) but in contrast to Coster and Adeoti (2015) and Fleischer et al. (2008), who find a positive effect, and Issahaku and Maharjan (2014) and Kurukulasuriya and Ajwad (2007),

[8] The results for cassava and rice are consistent with those in Issahaku and Maharjan (2014).

[9] As noted above, parameter estimates in a model including both *temp* and $(temp)^2$ are very imprecisely estimated, and it is not possible to determine whether the marginal effect of temperature on yield varies across the range. If there were evidence of a positive effect of temperature on maize revenues at the upper extent of the relevant range then one could argue more strongly that farmers are switching too soon.

who find no significant effect. The relative importance of experience and physical capability may well vary across households and crops, so it is unlikely that our results for age can be generalized.

The one anomalous result in Table 3 is that there is a negative and significant association between soil quality and net revenue from cassava and maize. One possible reason for this effect is that cassava and maize farmers over-invest in the improvement of fertile soils, but establishing the true cause of this effect is a subject for future research.

5. Simulating impact of climate change on agricultural revenue

We rely on the latest temperature and precipitation projections of the Intergovernmental Panel on Climate Change (IPCC) (Christensen *et al*., 2013) to simulate the impact of climate change on agricultural revenue in Ghana. These projections are based on Phase Five of the Coupled Model Inter-comparison Project (CMIP5), which collates results from 39 different global models. We use the projections for West Africa up to the year 2035. Three different IPCC scenarios are considered. Under the first and 'most optimistic' scenario, temperature is projected to increase by 0.7 degrees and precipitation by 8%. These increases represent the minimum projected increase in temperature and maximum projected increase in precipitation. The second scenario corresponds to the median increase in temperature (0.9 degrees) and in precipitation (1%). The third and 'least optimistic' scenario corresponds to the maximum projected increase in temperature (1.5 degrees) and maximum decline in precipitation (4%).

Table 4 presents the simulated change in the probability of selecting each crop under the three different scenarios, while Table 5 presents the simulated change in in revenue.[10] In

[10] An important caveat here is that given the way in which the projections have been constructed, it is not possible to compute standard errors around these simulations. The simulations also assume no change in any of the other characteristics affecting crop selection and revenue.

Appendices 2-3 we present a regional disaggregation of these results.[11] The main feature of Table 4 is that rising temperatures are associated with the increasing selection of millet and decreasing selection of other crops. Millet currently accounts for just over 6% of all plots: under the third and most extreme scenario this percentage is projected to increase tenfold. Maize currently accounts for just over 50% of all plots: under the third scenario this percentage is projected to fall by more than half. There are also substantial reductions in the cultivation of cassava, plantain, groundnuts and rice: in the third scenario these last two crops disappear almost entirely.

Table 5 presents the results for revenue, including simulations based on all three of the models in Table 3 (θ estimated, $\theta = 0$, and $\theta = 1$). For the first two of these models, which are nonlinear, it is necessary to compute marginal effects for the discrete changes in temperature and precipitation. For the Box-Cox model (θ estimated) we employ the two-stage smearing method of Abrevaya (2002), which is an extension of Duan (1983). For the log-linear model ($\theta = 0$) we use the extension of Duan proposed by Baum (2009). The signs of the effects are mostly consistent across the three models, but the sizes of the effects vary substantially, especially when comparing the linear model with the other two. Moreover, for millet, which is projected to become the most important crop in Ghana, the signs of the effects do vary across models. This means that finding the correct functional form for the revenue equation is essential for producing accurate climate change predictions. Given that the restrictions $\theta = 0$ and $\theta = 1$ can be rejected on our data we suggest that the simulations based on the Box-Cox model are the most reliable.[12]

[11] The appendices show that there is substantial inter-regional variation in the magnitude of the effects, as has been found in other countries – see for example Wang *et al*. (2009).

[12] In some cases the linear model predicts negative revenue for a particular crop. We have left these predictions in Table 5, but this is another reason for being sceptical about any predictions based on this model.

The most striking feature of the Box-Cox results in Table 5 is that there are only two cases in which there is any substantial change in revenue: under the first scenario there are moderate increases in cassava and rice revenue resulting from the increased precipitation. However, these two crops account for only a small proportion of total land use. For other crops (and for cassava and rice under the other scenarios) the predicted changes are very small. Another way of putting this result is that for each crop, the estimated effects of temperature and precipitation on revenue using the existing survey data are sometimes statistically significant but nevertheless generally quite small: the variation *within* the climatic range typical of each crop does not have large effects. However, as illustrated in Figures 1-2, there is substantial variation in the climatic conditions associated with each crop. Therefore, the effects of climate change on total agricultural revenue will be dominated by crop selection effects. In the baseline case corresponding to current climatic conditions, the estimated net revenue from millet for a household with average characteristics is about $240 per hectare. The next lowest figure is for plantain ($270), followed by cassava ($290), maize ($300), and then groundnuts and rice ($400). The Box-Cox results in Table 5 suggest that these figures are unlikely to change by very much, but the results in Table 4 suggest that groundnut and rice cultivation will plummet and millet will supplant maize as the predominant crop.

6. Summary and conclusion

We apply a Structural Ricardian Model to farm-level data from Ghana in order to estimate the impact of climate change on crop selection and revenue from production. We find that both crop selection and revenue are associated with a range of characteristics of the household and its land. Non-farm income, soil quality and the form of land tenure have substantial effects, and we find evidence suggesting that households with female heads are considerably disadvantaged. Conditional on these effects, local temperature and precipitation have large and asymmetric effects on crop selection decisions; they also have some effect on revenue from individual crops. One novel feature of our approach is the use of a Box-Cox transformation to model effects on revenue. We find that the simple functional forms that have been used in previous studies – for example a linear or log-linear function – can be rejected on our data. Alternative function forms lead to widely varying estimates of the size of the effects of temperature and precipitation on revenue, so this is not a trivial issue.

Our simulations of the effect of climate change are derived by combining the results of our statistical model with climate forecasts from the Intergovernmental Panel on Climate Change. These simulations suggest that climate change will have large effects on crop selection decisions: in particular, there will be substantial substitution of millet for maize (which is currently the most important food crop), and the cultivation of other crops such as groundnuts and rice will fall dramatically. Because of this adaptation, with farmers relying increasingly heavily on heat-tolerant millet, there are unlikely to be large effects on the revenue per hectare from individual crops. Although the overall volume of crop production might not change very much, overall revenue is likely to fall substantially, because millet is the least profitable of all existing crops, while groundnuts and rice are the most profitable.

Our results also suggest some ways in which the decline in revenue might be mitigated. Over the range of moderate temperatures at which maize cultivation is currently observed, higher temperatures do not reduce revenue, and it is possible that farmers switch too readily from maize to millet when temperatures rise, suggesting the need for incentives to encourage maize production. One policy might be to extend private land tenure, which is strongly associated with both a propensity to cultivate maize and with revenues from maize cultivation. However, even if such measures do mitigate the decline in revenue, Ghana may have to look to alternative, non-agricultural sources of income in the future.

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Table 1

Descriptive statistics

	cassava	*groundnut*	*maize*	*millet*	*plantain*	*rice*
			Mean (standard deviation in parentheses)			
revenue ÷ 100	2.85 (3.78)	3.96 (4.27)	2.96 (4.26)	2.36 (2.26)	2.67 (4.10)	4.03 (5.11)
temp	26.1 (0.50)	26.6 (0.40)	26.3 (0.60)	26.8 (0.40)	25.9 (0.60)	26.5 (0.40)
precip ÷ 1000	1.39 (0.11)	1.21 (0.13)	1.31 (0.14)	1.20 (0.10)	1.45 (0.08)	1.44 (0.10)
non-farm-income ÷ 1000	3.75 (7.42)	2.64 (7.53)	4.02 (13.2)	1.45 (3.66)	6.61 (32.0)	3.36 (10.7)
age	50 (15)	47 (16)	48 (15)	49 (17)	49 (14)	46 (16)
			Percentage			
soil	91.9	30.8	77.7	43.8	97.8	49.8
tenure	29.5	6.1	21.9	2.7	26.7	10.9
male	70.5	81.2	80.2	83.2	70.9	81.3
			Number of observations			
	762	1019	3255	403	457	410

Table 2

Marginal effects in the crop selection model

	cassava	*groundnuts*	*maize*	*millet*	*plantain*	*rice*
tenure	0.011 *0.010*	–0.046** *0.014*	0.069** *0.019*	–0.038** *0.009*	–0.013* *0.007*	0.018 *0.012*
non-farm-income	-2.4×10^{-7} 4.0×10^{-7}	-7.2×10^{-7} 7.4×10^{-7}	3.0×10^{-6}** 1.0×10^{-6}	-3.0×10^{-6}* 1.5×10^{-6}	5.2×10^{-7}** 4.0×10^{-7}	5.8×10^{-7} 3.8×10^{-7}
soil	0.056** *0.011*	–0.216** *0.013*	0.111** *0.016*	–0.011* *0.006*	0.081** *0.004*	–0.021** *0.007*
age	0.0010** *0.0003*	–0.0010* *0.0003*	–0.0000 *0.0004*	0.0002 *0.0002*	0.0001 *0.0002*	–0.0005* *0.0002*
male	–0.040** *0.010*	–0.006 *0.011*	0.050** *0.015*	0.020** *0.007*	–0.018* *0.008*	–0.006 *0.008*

** and ** signify significance levels at 5% and 1%, respectively. Heteroscedasticity-robust standard errors are in italics.*

Table 3
Conditional net revenue regression coefficients (part 1)

model	cassava Box-Cox	cassava log-linear	cassava linear	groundnuts Box-Cox	groundnuts log-linear	groundnuts linear	maize Box-Cox	maize log-linear	maize linear
temp	1.423	0.568	198.7**	0.265	-0.055	141	0.521	0.28*	104.5*
	2.8	*0.4*	*74.4*	*0.2*	*0.3*	*113.3*	*0.4*	*0.2*	*58.7*
precip	0.181**	0.073**	22.7**	0.039	0.011	10.2	0.028	0.016	4.3
	12.1	*0.02*	*5.2*	*1.0*	*0.02*	*6.6*	*2.5*	*0.01*	*3.8*
$(precip)^2$	-6.9×10^{-5}**	-2.8×10^{-5}**	-0.01**	-1.6×10^{-5}	-5.1×10^{-6}	-0.004	-7.9×10^{-6}	-4.7×10^{-6}	-0.001
	12.5	8.9×10^{-6}	*0.002*	*1.3*	6.7×10^{-6}	*0.002*	*1.5*	3.7×10^{-6}	*0.001*
tenure	1.879**	0.837**	176.3**	-0.662*	-0.295	-106.6	0.35**	0.193**	67.8**
	35.1	*0.1*	*39.6*	*3.1*	*0.2*	*75.1*	*9.9*	*0.1*	*22.9*
soil	-2.061*	-0.937*	-162.1*	0.577	0.381	-9.9	-1.028**	-0.568**	-185*
	2.8	*0.5*	*98.0*	*0.8*	*0.4*	*138.5*	*8.4*	*0.2*	*91.4*
age	0.005	0.002	-0.3	0.005	0.003	0.03	-0.011**	-0.006**	-2.5**
	0.2	*0.01*	*1.1*	*0.4*	*0.004*	*1.3*	*8.7*	*0.002*	*0.7*
male	1.917**	0.812**	189.3**	1.783**	0.823**	263.6**	1.341**	0.778**	177.2**
	18.9	*0.2*	*42.8*	*68*	*0.1*	*30.8*	*104.1*	*0.1*	*24.8*
$r_{cassava}$				1.626	0.488	442.1	1.044*	0.585*	170.3
				1.0	*0.9*	*295.2*	*2.9*	*0.3*	*119.6*
$r_{groundnuts}$	-0.999	-0.4	-240.6				2.3	0.2	87.3
	0.2	*0.9*	*171.1*				*0.5*	*0.3*	*125.9*
r_{maize}	-1.885*	-0.772*	-272.4**	0.009	-0.039	41.3			
	5.6	*0.3*	*81.7*	*0.001*	*0.2*	*76.9*			
r_{millet}	-3.757	-1.428	-611.9**	-1.966*	-0.757	-447.9**	-0.64	-0.286	-237.6*
	2.0	*1.1*	*234.4*	*4.6*	*0.4*	*165.2*	*1.3*	*0.3*	*132*
$r_{plantain}$	0.203	0.337	-293.2	-3.095*	-1.793*	-144.1	1.816**	0.971**	352.3**
	0.02	*0.7*	*179*	*3.6*	*0.9*	*271.9*	*15.1*	*0.3*	*104.7*
r_{rice}	0.822	0.616	-568	2.583	1.572	73.7	-3.811*	-1.826	-1201.0**
	0.01	*3.4*	*701.7*	*0.5*	*2.0*	*603.2*	*3.9*	*1.1*	*368.3*
θ	0.178**			0.145**			0.113**		
σ	3.3			2.2			2.2		

** and ** signify significance at 5% and 1%, respectively. Figures in italics are χ^2 test statistics (in the Box-Cox models) or standard errors (in other models).*

Table 3
Conditional net revenue regression coefficients (part 2)

	millet			*plantain*			*rice*		
model	*Box-Cox*	*log-linear*	*linear*	*Box-Cox*	*log-linear*	*linear*	*Box-Cox*	*log-linear*	*linear*
temp	-2.431*	-1.285*	-368.5*	-4.545*	-2.612*	-495.7	-1.792**	-1.188*	-600.1**
	4.5	*0.6*	*162.8*	*4.1*	*1.3*	*269.9*	*8.1*	*0.5*	*277.7*
precip	0.081	0.046	31.6	-0.402*	-0.243*	-28.5	-0.1*	-0.064	-37.9**
	0.5	*0.1*	*29.7*	*4.1*	*0.1*	*25.9*	*4.4*	*0.04*	*19.2*
$(precip)^2$	-2.9×10^{-5}	-1.7×10^{-5}	-0.01	1.4×10^{-4}	8.5×10-5*	0.01	3.5×10^{-5}*	2.3×10^{-5}	0.01**
	0.5	3.1×10^{-5}	*0.01*	*3.8*	4.1×10^{-5}	*0.01*	*4.3*	*1.3×10-5*	*0.01*
tenure	-0.778	-0.442	-77.1	0.689	0.367	70.5	-0.607	-0.404	-201.3
	1.8	*0.4*	*125.9*	*2.2*	*0.3*	*68.1*	*3.4*	*0.2*	*119.9*
soil	-0.073	-0.017	-35.8	7.288	4.061*	723.8	-0.617	-0.489	68.3
	0.01	*0.5*	*144.4*	*3.1*	*1.8*	*418.2*	*1.5*	*0.4*	*201.5*
age	-0.003	-0.002	-0.2	0.043	0.025	5.0	0.001	0.001	0.4
	0.1	*0.01*	*2.1*	*2.9*	*0.02*	*3.2*	*0.03*	*0.004*	*1.6*
male	0.969**	0.551**	125.7*	-1.36	-0.825	-95.6	0.888**	0.617**	120.9
	8.4	*0.2*	*50.3*	*1.4*	*0.7*	*156.4*	*12.2*	*0.2*	*70.5*
$r_{cassava}$	5.029	2.775	1200.4	-11.846**	-7.024**	-1049.5*	-5.304	-3.417	-2008.3*
	1.6	*2.9*	*960.9*	*9.2*	*2.4*	*488.4*	*3.6*	*2.0*	*828.1*
$r_{groundnuts}$	-2.884*	-1.522*	-457.5*	-0.521	-0.718	-260.1	-3.097**	-2.134*	-772.8
	5.5	*0.7*	*175.4*	*0.01*	*3.7*	*807.5*	*8.7*	*0.8*	*334.3*
r_{maize}	-0.892	-0.51	-129.6*	0.095	0.071	1.8	-0.221	-0.154	-84.1
	2.1	*0.3*	*65.2*	*0.01*	*0.7*	*162.4*	*0.3*	*0.3*	*135.8*
r_{millet}				-1.277	-0.545	-539.8	-1.461	-1.073	-22.5
				0.03	*3.9*	*821.3*	*1.8*	*1.1*	*559.5*
$r_{plantain}$	-11.977*	-6.236*	-1913.9*				-4.253	-2.814	-1533.1
	4.3	*2.8*	*747.3*				*3.5*	*1.7*	*963.1*
r_{rice}	2.072	1.038	630.9	34.908	20.097	5319.2*			
	0.2	*3.0*	*852.5*	*2.3*	*14.6*	*2674.1*			
θ	0.118**			0.126**			0.073*		
σ	1.549			2.674			1.563		

** and ** signify significance at 5% and 1%, respectively. Figures in italics are χ^2 test statistics (in the Box-Cox models) or standard errors (in other models).*

Table 4

Simulated change in probability of selecting a crop under various IPCC scenarios

	cassava	*groundnut*	*maize*	*millet*	*plantain*	*rice*
Baseline	12.1%	16.2%	51.6%	6.4%	7.2%	6.5%
Scenario I	–7.1%	–8.5%	–6.1%	+24.3%	–4.3%	+1.7%
Scenario II	–6.7%	–12.8%	–13.0%	+38.1%	–1.7%	–3.9%
Scenario III	–8.6%	–15.4%	–28.8%	+56.4%	+2.3%	–6.0%

The baseline represents the estimated probability of selecting a particular crop for the average household under current conditions.

Table 5

Simulated change in net revenue under various IPCC scenarios

	cassava			*groundnuts*			*maize*		
Model	*Box-Cox*	*linear*	*log-linear*	*Box-Cox*	*linear*	*log-linear*	*Box-Cox*	*linear*	*log-linear*
Baseline	286.8	283.9	309.3	393.8	395.6	398.8	294.6	296.4	299.2
Scenario I	+98.9	+260.0	+208.6	+4.2	+36.6	+12.9	+11.0	+238.7	–2.0
Scenario II	+2.0	+202.7	+0.2	–0.1	+124.2	+0.5	+0.71	+115.9	–0.6
Scenario III	+19.3	+177.8	+50.0	+2.5	+208.2	+0.4	–1.0	+65.9	+2.8

	millet			*plantain*			*rice*		
Model	*Box-Cox*	*linear*	*log-linear*	*Box-Cox*	*linear*	*log-linear*	*Box-Cox*	*linear*	*log-linear*
Baseline	235.8	236.7	236.6	274.1	268.3	305.1	406.7	404.4	415.4
Scenario I	+14.0	–623.3	+32.1	+172.9	–899.9	+357.3	+154.2	–221.2	+106.4
Scenario II	–0.0	–360.5	+0.7	+18.3	–524.5	–12.5	+5.0	–534.5	–2.0
Scenario III	+5.2	+66.8	+4.0	+68.8	–404.2	+201.7	+13.1	–867.9	+43.2

The baseline represents the estimated revenue from a particular crop for the average household under current conditions.

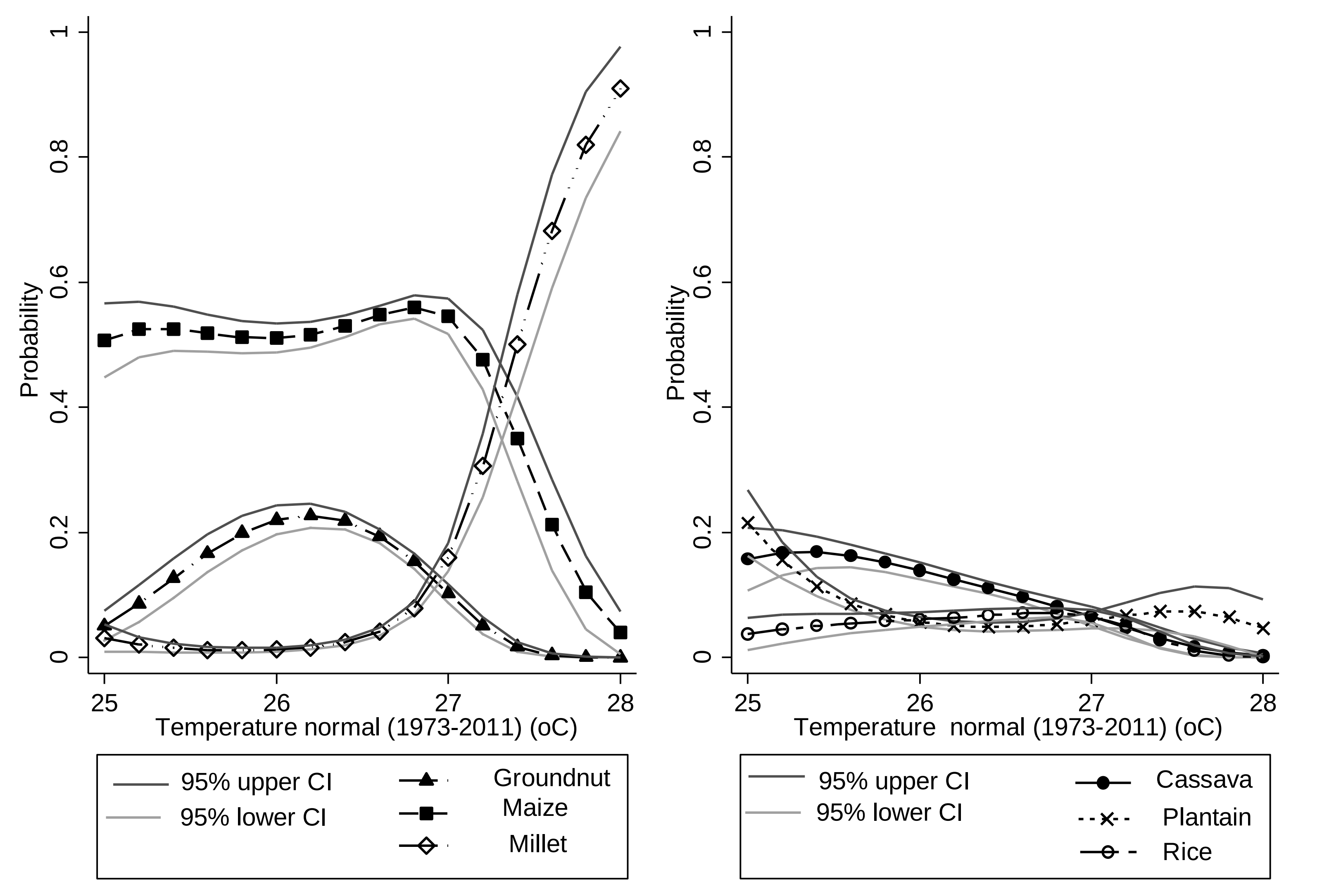

Fig. 1. Predicted probability of selecting a crop at various temperatures

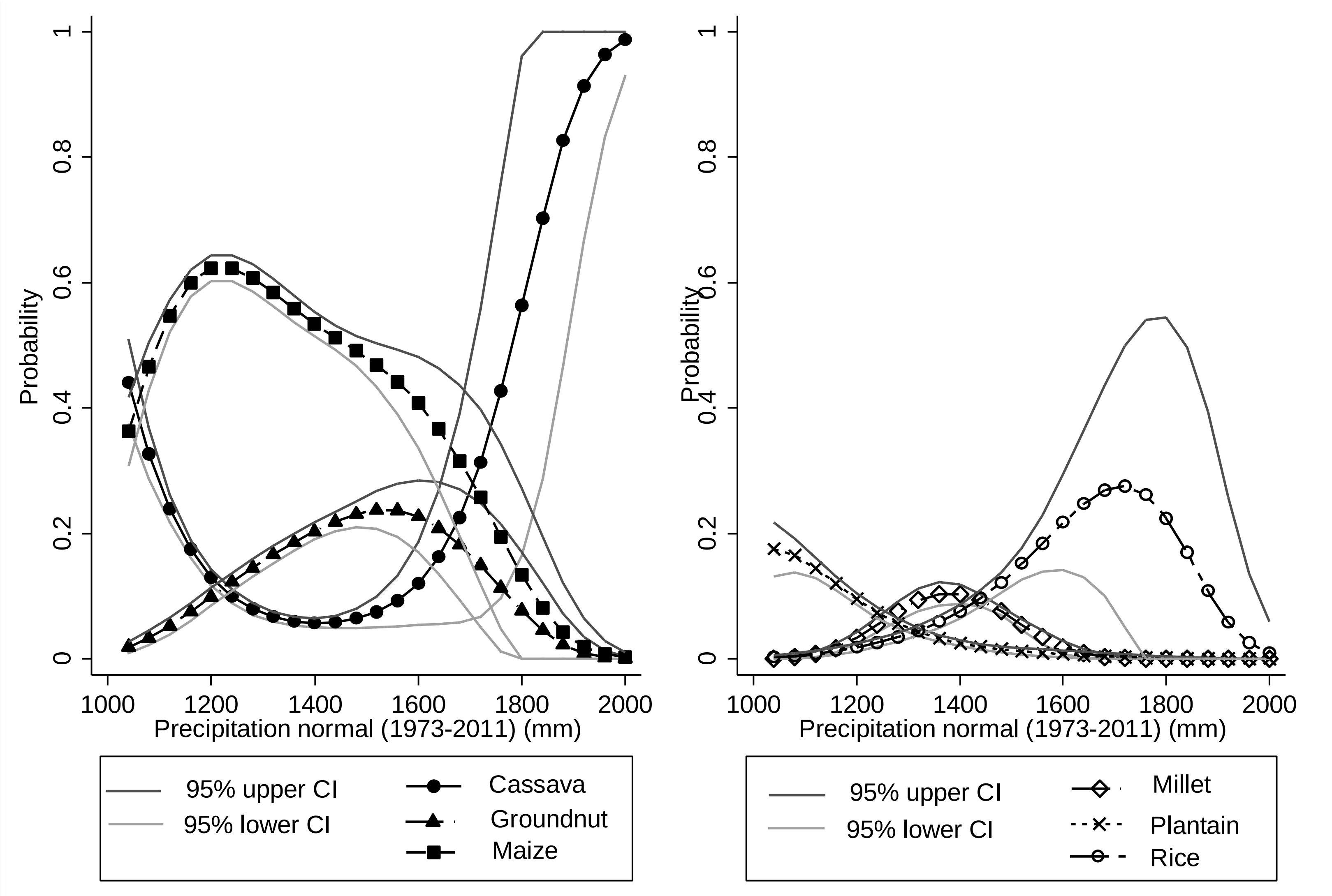

Fig. 2. Predicted probability of selecting a crop at various levels of precipitation

Appendix 1: Parameter estimates in the crop selection model (N = 6306)

	cassava	*groundnuts*	*millet*	*plantain*	*rice*
temp	12.1	72.9**	–81.8**	–44.4**	22.2*
	8.7	*8.2*	*10.6*	*9.2*	*11.1*
($temp$)^2	–0.3	–1.4**	1.6**	0.8**	–0.4*
	0.2	*0.2*	*0.2*	*0.2*	*0.2*
precip	–0.07**	0.03**	0.11**	–0.02*	0.02
	0.01	*0.01*	*0.02*	*0.01*	*0.01*
($precip$)^2	2.3×10^{-5}**	-8.1×10^{-6}**	-3.7×10^{-5}**	6.6×10^{-6}*	-4.4×10^{-6}
	3.4×10^{-6}	2.8×10^{-6}	6.3×10^{-6}	3.7×10^{-6}	5.1×10^{-6}
tenure	0.01	–0.5**	–1.1**	–0.3*	0.04
	0.1	*0.2*	*0.3*	*0.1*	*0.2*
non-farm	-4.4×10^{-6}	-1.6×10^{-5}**	-6.8×10^{-5}*	5.8×10^{-6}*	3.2×10^{-6}
income	4.3×10^{-6}	6.1×10^{-6}	2.8×10^{-5}	3.0×10^{-6}	5.7×10^{-6}
soil	0.6**	–1.7**	–0.7**	4.0**	–0.8**
	0.2	*0.1*	*0.1*	*1.0*	*0.1*
age	0.008**	–0.006*	0.002	0.003	–0.01*
	0.003	*0.003*	*0.003*	*0.003*	*0.004*
male	–0.5**	–0.1	0.4*	–0.4**	–0.1
	0.1	*0.1*	*0.2*	*0.1*	*0.1*

Count R^2 = 0.53

Joint significance of regressors: $\chi^2(45) = 2136$ [$p < 0.01$]

*The default category is maize. * and ** signify significance at 5% and 1%, respectively. Heteroscedasticity-robust standard errors are in italics.*

Appendix 2: Simulated change in probability of selecting a crop disaggregated by region

	cassava	*groundnut*	*maize*	*millet*	*plantain*	*rice*
			Western Region			
Baseline	38.4%	1.4%	42.4%	0.1%	17.3%	0.4%
Scenario I	–26.9%	+0.3%	+23.3%	+6.2%	–3.7%	+0.7%
Scenario II	–20.7%	–1.0%	+9.4%	+3.8%	+8.4%	+0.0%
Scenario III	–29.0%	–1.4%	–17.7%	+13.4%	+35.0%	–0.3%
			Central Region			
Baseline	15.0%	7.3%	66.5%	0.8%	8.3%	2.0%
Scenario I	–10.0%	+0.6%	+1.3%	+9.8%	–4.6%	+3.0%
Scenario II	–8.9%	–4.0%	+2.8%	+10.1%	–0.2%	+0.3%
Scenario III	–12.6%	–7.1%	–29.1%	+44.1%	+6.2%	–1.5%
			Greater Accra Region			
Baseline	11.6%	6.4%	56.7%	16.7%	5.9%	2.6%
Scenario I	–8.4%	–3.6%	–9.4%	+24.3%	–2.8%	–0.1%
Scenario II	–7.3%	–5.4%	–10.6%	+23.9%	+1.0%	–1.6%
Scenario III	–9.9%	–6.4%	–33.5%	+44.4%	+7.9%	–2.4%
			Volta Region			
Baseline	10.6%	21.7%	53.9%	2.2%	2.4%	9.1%
Scenario I	–6.4%	–13.4%	–0.4%	+13.4%	–0.8%	+7.6%
Scenario II	–7.1%	–19.3%	–8.7%	+38.6%	+0.8%	–4.2%
Scenario III	–9.6%	–21.7%	–42.2%	+80.1%	+2.3%	–9.0%
			Eastern Region			
Baseline	21.4%	2.2%	59.5%	0.9%	15.1%	0.8%
Scenario I	–16.0%	+1.0%	–8.6%	+31.6%	–8.9%	+0.9%
Scenario II	–13.3%	–1.1%	–12.8%	+28.9%	–1.6%	–0.1%
Scenario III	–16.0%	–2.1%	–29.1%	+42.1%	+5.7%	–0.6%
			Ashanti Region			
Baseline	13.1%	5.2%	65.6%	2.1%	10.7%	3.3%
Scenario I	–4.0%	+13.3%	–7.3%	–0.6%	–8.9%	+7.4%
Scenario II	–5.3%	+9.8%	–0.2%	+0.4%	–7.7%	+3.0%
Scenario III	–7.4%	+1.2%	+4.9%	+6.5%	–5.8%	+0.6%
			Brong-Ahafo Region			
Baseline	19.9%	3.7%	53.3%	0.6%	19.5%	2.9%
Scenario I	–9.5%	+6.6%	+12.8%	+1.4%	–14.9%	+3.7%
Scenario II	–6.6%	+2.2%	+10.6%	+5.9%	–11.9%	–0.2%
Scenario III	–7.1%	–1.9%	+6.2%	+11.6%	–7.0%	–2.0%

Appendix 2 (continued)

	cassava	*groundnut*	*maize*	*millet*	*plantain*	*rice*
			Northern Region†			
Baseline	6.1%	17.0%	57.0%	7.3%	2.2%	10.3%
Scenario I	–1.7%	–10.2%	–12.0%	+21.1%	–1.1%	+3.9%
Scenario II	–4.4%	–14.7%	–25.2%	+50.8%	–0.6%	–5.9%
Scenario III	–5.7%	–17.0%	–50.2%	+83.7%	–0.7%	–10.1%
			Upper East Region†			
Baseline	2.0%	21.1%	38.6%	23.6%	0.5%	14.2%
Scenario I	–1.4%	–20.2%	–25.3%	+55.0%	–0.2%	–7.9%
Scenario II	–2.0%	–21.0%	–37.2%	+74.6%	–0.4%	–13.9%
Scenario III	–2.0%	–21.1%	–38.6%	+76.4%	–0.5%	–14.2%
			Upper West Region†			
Baseline	2.2%	45.1%	40.3%	5.8%	0.0%	6.6%
Scenario I	–1.5%	–31.0%	–12.9%	+43.4%	0.0%	+2.0%
Scenario II	–1.8%	–41.7%	–21.8%	+69.5%	0.0%	–4.1%
Scenario III	–2.2%	–45.1%	–38.7%	+92.5%	0.0%	–6.5%

† *In these regions, some simulated observations have a higher temperature than any in-sample observation, so the results should be treated with caution.*

Appendix 3: Simulated change in crop net revenue disaggregated by region (Box-Cox model)

	cassava	*groundnut*	*maize*	*millet*	*plantain*	*rice*
			Western Region			
Baseline	238.6	§	250.7	§	328.3	§
Scenario I	–94.7	§	–54.8	§	+213.3	§
Scenario II	–17.8	§	–7.8	§	+72.3	§
Scenario III	+100.5	§	+34.6	§	–138.7	§
			Central Region			
Baseline	260.2	§	243.4	§	§	§
Scenario I	+73.0	§	–16.5	§	§	§
Scenario II	+4.6	§	–2.4	§	§	§
Scenario III	–4.6	§	+10.7	§	§	§
			Greater Accra Region			
Baseline	447.0	§	252.0		§	§
Scenario I	+334.5	§	–20.5		§	§
Scenario II	+28.5	§	–3.0		§	§
Scenario III	–83.9	§	+13.2		§	§
			Volta Region			
Baseline	352.3	385.8	279.1	§	§	§
Scenario I	+483.0	+60.8	+19.4	§	§	§
Scenario II	+30.3	+6.3	+1.6	§	§	§
Scenario III	–64.8	–22.0	–4.3	§	§	§
			Eastern Region			
Baseline	315.8	§	244.0	§	263.8	§
Scenario I	–45.5	§	–37.4	§	+890.7	§
Scenario II	–10.2	§	–5.3	§	+32.2	§
Scenario III	+60.5	§	23.0	§	–49.3	§
			Ashanti Region			
Baseline	189.8	§	291.0	§	160.4	§
Scenario I	+244.4	§	+19.5	§	–114.1	§
Scenario II	+19.1	§	+2.1	§	–38.9	§
Scenario III	–54.4	§	–7.2	§	+412.7	§
			Brong-Ahafo Region			
Baseline	328.9	§	277.4	§	406.3	§
Scenario I	+86.4	§	–17.9	§	+553.1	§
Scenario II	+2.5	§	–2.7	§	+12.2	§
Scenario III	+11.3	§	+12.5	§	+48.3	§

Appendix 3 (continued)

			Northern Region†			
Baseline	§	486.8	300.6	§	§	494.1
Scenario I	§	+17.5	+50.9	§	§	–3.9
Scenario II	§	+1.4	+5.5	§	§	–8.6
Scenario III	§	–3.6	–20.1	§	§	+63.7
			Upper East Region†			
Baseline	§	268.1	315.8	229.0	§	307.0
Scenario I	§	+41.0	+73.5	+44.9	§	–46.3
Scenario II	§	+4.6	+8.1	+4.3	§	–9.3
Scenario III	§	–17.0	–29.7	–14.4	§	+53.3
			Upper West Region†			
Baseline	§	417.0	424.2	§	§	§
Scenario I	§	–26.9	+14.1	§	§	§
Scenario II	§	–3.8	+1.3	§	§	§
Scenario III	§	+16.6	–4.0	§	§	§

† *In these regions, some simulated observations have a higher temperature than any in-sample observation, so the results should be treated with caution.*

§ *Given the small sample sizes at the sub-national level, results are reported only for crops accounting for at least 10% of the baseline case in Appendix 2.*