WPS4161

Changing Farm Types and Irrigation as an Adaptation to Climate Change in Latin American Agriculture[1]

Robert Mendelsohn
School of Forestry and Environmental Studies, Yale University USA
and
Niggol Seo
University of Aberdeen Business School, UK

Abstract

This paper estimates a model of a farm that treats the choice of crops, livestock, and irrigation as endogenous. The model is composed of a multinomial choice of farm type, a binomial choice of irrigation, and a set of conditional land value functions. The model is estimated across over 2000 farmers in Latin America. The results quantify how farmers adapt their choice of farm type and irrigation to their local climate. The results should help governments develop effective adaptation policies in response to climate change and improve the forecasting of climate impacts. The paper compares the predicted impacts of climate change using both endogenous and exogenous models of farm choice.

World Bank Policy Research Working Paper 4161, March 2007

[1] Funding of this project was provided by the World Bank. We thank Emilio Ruz, Flavio Avila, Jorge Lozanoff, Luis José María Irias, Magda Aparecida de Lima, Jorge Granados, Jorge González, Flavio Játiva, Alfredo Albin, Bruno Lanfranco, Rafael Pacheco for their contribution to this project. This project was funded by the Research Committee of the World Bank under the study 'Climate Change and Rural Development' that was tasked managed by Ariel Dinar.

1. Introduction

This paper develops a Ricardian farm model that allows farmers to choose the type of farm and irrigation based on the net productivity of each choice. Although the agriculture literature has carefully developed approaches to study the adoption of irrigation technology (Caswel and Zilberman 1986; Dinar and Yaron 1990; Negri and Brooks 1990; Dinar and Zilberman 1991; Dinar, Campbell, and Zilberman 1992), the literature has not explored how adoption may be related to climate. There have been several agronomic studies in Latin America of selected crops in a selected country (Downing 1992; De Siquerira et al. 1994; Magrin et al. 1997; Hofstadter et al. 1997; Conde et al. 1997) that suggest individual crops would be sensitive to warming. But this agronomic literature does not explore how farmers themselves would react to climate change. Mathematical programming (MP) has been used to explore how predicted yield losses from climate change would cause American farmers to change crops (Adams et al. 1994) and switch between crops and livestock (Adams et al. 1999). However, the MP approach has only been developed for the US and it places all the burden of including adaptation on the analyst. To the extent that the analyst is unaware of substitutions farmers can make or is unaware of reasons farmers cannot make substitutions, there is a possibility of error.

This paper presents an alternative methodology for measuring adaptation to climate by relying on cross sectional evidence. Cross sectional evidence has been widely used to measure the link between land value (or net revenue) and climate (Mendelsohn et al. 1994; 1996; 1999; 2001; Mendelsohn and Dinar 2003; Sanghi 1998; Seo et al. 2005; Kurukulasuriya et al 2006; Kurukulasuriya and Mendelsohn 2006a; Seo and Mendelsohn

2006). These "Ricardian" results provide a consistent welfare measure of the long run impacts of climate on agriculture. However, the Ricardian studies do not provide insight into how farmers are adapting to climate. By explicitly modeling adaptation, this paper seeks to explain the Ricardian results and also bridge the gap between the (MP) approach and the Ricardian approach.

The theoretical model of the farm allows a farmer to choose among crops, livestock, and irrigation to maximize profit. Although many farmers in developed countries either specialize in crops or livestock, many farmers in developing countries choose to do both activities. We first explore whether farmers who face different climates tend to choose different types of farming. Following Kurukulasuriya and Mendelsohn 2006b, the model is extended to include the choice of irrigation. We then explore the conditional net revenue the farmer should expect given the choice of farm type and irrigation.

The paper is divided into five parts. The next section develops the theory. The third section describes the survey of over 2000 subsistence and commercial farmers across 7 Latin American countries and other data sources. The fourth section discusses the cross sectional results. The fifth section presents forecasts of impacts from a set of future climate scenarios. We compare the forecasts one would make assuming these choices are endogenous with the results if one assumed the choices were fixed. We conclude the paper with the policy implications and the limitations of the paper.

2. Theory

We assume that farmers choose amongst three types of farms: crops only, livestock only, and a combination of crops-livestock. For each of the farm types that have crops, the farmer can also choose to do dryland farming or use irrigation. Given these choices, the farmer combines inputs to make outputs that maximize land value. We assume that the farmer will choose the combination of farm type and irrigation that maximizes expected net revenues.

For example, in Figure 1, we show a hypothetical relationship between farm type and climate. The picture suggests that each farm type is ideal for a particular climate range. As climate changes, farmers switch from one farm type to another. The overall response function captures this switching. However, by explicitly modeling the switching, analysts can see what changes farmers are making to stay on the maximum profit locus. .

The profit each farmer i obtains from choosing farm type j (j=1, 2, or 3) is the following:

$$\pi_{ij} = V(K_j) + \varepsilon_1(K_j) \tag{1}$$

where K is a vector of exogenous characteristics of the farm. For example, K could include climate and soils. We identify the choice of farm type with crop prices that reflect the attractiveness of planting crops versus livestock. The profit function 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 farm type that gives him the highest profit. In other words, the farmer will choose farm type j over all other farm types k if:

$$\pi^*(K_{ji}) > \pi^*(K_{ki}) \text{ for } \forall \text{ k} \neq \text{j.[or if } \varepsilon_1(K_{ki}) - \varepsilon_1(K_{ji}) < V(K_{ji}) - V(K_{ki}) \text{ for k} \neq \text{j]} \quad (2)$$

More succinctly, farmer *i*'s problem is:

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

The probability P_{ji} of the *jth* farm type being chosen is

$$P_{ji} = \Pr[\varepsilon_1(K_{ki}) - \varepsilon_1(K_{ji}) < V_j - V_k] \ \forall \text{ k} \neq \text{j where } \mathrm{V_j = V(K_{ji})} \quad (4)$$

Assuming ε_1 is independently Gumbel distributed and $V_k = K_{ki}\gamma_k + \alpha_k$, the probability that farmer *i* will choose farm type j among the 3 farm types is (Chow 1983; McFadden 1981):

$$P_{ji} = \frac{e^{K_{ji}\gamma_j}}{\sum_{k=1}^{3} e^{K_{ki}\gamma_k}} \quad . \quad (5)$$

The parameters can be estimated by 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). The probability of choice is identified by both cross price terms for crops and livestock and adding up constraints across the probabilities.

Conditional on choosing crops, the farmer can also choose irrigation. As with the farm type model, we assume that the farmer chooses irrigation only if it is more profitable. We estimate a dichotomous choice model of irrigation, Y, where Y=1 is irrigation and Y=0 is dryland farming:

$$Y_i = \beta^1 X + \varphi \tag{6}$$

where X is a k-vector of regressors for the irrigation choice and φ is an error term. The vector X includes soils and climate. The irrigation choice is identified by the soil clay. Clay soils generally make irrigation difficult because the soils become water logged.

In the third stage, we estimate a conditional profit function for each type of farming based on the available exogenous variables, Z:

$$\prod_i = \gamma^j \mathrm{Z}^i + \mu_j \text{ if } \mathrm{Y} = j \tag{7}$$

where Y_j is a latent variable explaining the choice of farm type/irrigation, Π_j is the net profit of farms of type j, Z^j is an m-vector of regressors that determine land value, γ^j is an m-vector of coefficients for farm type j, and the error terms ε, φ, and μ_j are jointly normally distributed, independently of X and Z, with zero expectations.

$$\varphi \sim N(0,1) \tag{8a}$$

$$\mu_j \sim N(0, \sigma_j) \tag{8b}$$

$$\mathrm{corr}(\varepsilon, \mu_j) = \rho_1 \tag{8c}$$

$$\mathrm{corr}(\varphi, \mu_j) = \rho_2 \tag{8d}$$

where u_j =error from the third stage, ε_j =error from the first stage, φ_j =error from the second stage, σ_j =standard error from the unconditioned land value regression, r_j =correlation between the choice error and the land value regression error.

Because of selection bias, it is possible that the unobserved profitability of a choice is correlated with the selection of that choice (Heckman 1979). Since the farmer maximizes net revenue conditional on the choice of farm type, the error in the land value equation may be correlated with the errors in the choice equations. According to Dubin and McFadden (1984), with the assumption of the following linearity condition:[2]

$$E(u_j \mid \varepsilon_1,\ldots,\varepsilon_J) = \sigma_j \cdot \sum_{j=1}^{J} r_j(\varepsilon_j - E(\varepsilon_j)) \text{ with} \sum_{\mathrm{j=1}}^{\mathrm{J}} r_j = 0 \tag{9}$$

The conditional profit functions can be consistently estimated as:

---

[2] See Bourguignon et al. (2004) for the details of the selection bias corrections from the multinomial choice. They find that Dubin and McFadden's method is preferable to the most commonly used Lee method, as well as to the Dhal's semi-parametric method in most cases. Monte Carlo experiments also showed 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.

$$\pi_j = x_j\beta_j + x_j^2\delta_j + \sigma_j \cdot \sum_{i\neq j}^{J} r_i \cdot \left(\frac{P_i \cdot \ln P_i}{1-P_i} + \ln P_j \right) + w_j \tag{10}$$

where the third term on the right hand side is the correction term and w_j is the error term.

In this analysis, we employ land value as the measure of net productivity. With perfect competition for land, free entry and exit will drive excess profits to zero on the margin. (Ricardo 1817) In this case, land rents will equal net income per hectare. Land value will reflect the present value of the net income of each farm:

$$V_{land} = \int_0^\infty \pi_t^* \cdot e^{-rt} dt \tag{11}$$

, where r is the market interest rate. (Mendelsohn et al. 1994)

Land values provide a better measure of climate response because they reflect the expectation of net revenues across many years. In contrast, annual net revenues reflect annual outcomes that vary year by year such as weather and prices. Since we are interested in this analysis in climate not weather impacts, the land value measure is more relevant. The land value measure also captures the farmer's expectations about other things that might change in the future. For example, if farmers expect that technical change will enable them to cultivate the same plot more productively in the future, it will be reflected in land value.

In this model, the expected value of a farm, W, is the sum of the probabilities, P_k, of each farm type times the conditional net revenue of that farm type. That is:

$$W(C) = \sum_{k=1}^{6} P_k(C) * V_k(C) \quad (12)$$

The change in welfare, ΔW, resulting from a climate change from C_A to C_B can be measured as follows.

$$\Delta W_i = W_i(C_B) - W_i(C_A) \quad (13)$$

3. Data and Background

Farm surveys were pretested and then finalized[3]. Each survey was translated to Spanish or Portuguese depending on the country. Farm surveys were collected by country teams from seven countries in Latin America[4]. The seven countries include: Argentina, Brazil, Chile, Colombia, Ecuador, Uruguay, and Venezuela. Random samples of districts were selected to observe a set of farms over a wide range of climates within each country. In each country, 15-30 clusters were selected and 20-30 households were interviewed in each cluster. Cluster sampling was done to control the cost of the survey. The farm surveys ask questions about farming activities, including crop and livestock production and costs. The survey was conducted from July 2003 to June 2004. Surveys also record the climate and weather related perceptions of the farmers. Altogether, a total of 2003

---

[3] Survey forms are available from the authors.

[4] We wish to thank Flavio Avila for managing the 7 country data collection process. We also wish to thank the team leaders of the collection process in each country: A. Albin, R. Bruno, J. Gonzalez, P. Granados, L. Irias, P. Jativo, J. Lozanoff, R. Pacheco.

farms were surveyed.

Climate data come from two sources: temperature observations came from US Defense Department Satellites and the rainfall observations came from ground station data of the World Meteorological Organization. The satellite temperature measures proved superior to the weather station observations at least for rural areas of the world (Mendelsohn et al 2005). The satellites can observe the entire surface of the earth whereas many rural areas do not have a weather station nearby and so require interpolation. Unfortunately, the satellites cannot directly measure precipitation and so the weather station data is the best that can be done at the moment.

Soil data were obtained from the FAO digital soil map of the world CD ROM. The data was extrapolated to the district level using Geographical Information System. The data set reports 116 dominant soil types organized into 26 major groups. We extract texture and slope of the soils at the district level.

The analysis relies upon land values and farm characteristics as reported by the interviewed farmer. In many parts of Latin America, land has been reallocated by the government. Land use is also restricted in many cases. For example, farmers in Brazil face official limitations on land clearing. The analysis was not able to control for all of these imperfections in the land market. However, separate analyses comparing Ricardian regressions that use land values and net revenues for the dependent variable lead to very similar results, suggesting the land value data is consistent and unbiased.

4. Empirical Results

The study identified three types of farms in the region: crop only, livestock only, and crops/livestock together. We further break down farms that grow crops by whether or not they use irrigation. Table 1 measures how many farms of each type were in the sample. Over half of the farms have both livestock and crops, almost one third of the farms rely solely on crops, and only 13% of the farms just raise animals. Only 26% of the farms with crops use irrigation. Three fourths of the farms growing crops use dryland farming.

Our first analysis seeks to explore how different exogenous factors and specifically climate affect the choice of farm type. We conduct a multinomial logit omitting the choice of livestock-only farms for comparison. The results are displayed in Table 2. All eight climate coefficients are significant in the cop-only regression and all but the linear term on summer temperature are significant in the mixed crop-livestock regression. In order to help interpret the climate coefficients, Table 3 presents the marginal log odds ratios for annual temperature and precipitation. Crop-only farms are less common in places with warmer annual temperatures and the effect is significant at the 5% level. In contrast, precipitation does not influence the choice of crop-only versus livestock only farms. In contrast, mixed crop-livestock farms are more frequent in warmer places and this effect is significant. The results imply that livestock-only farms are more likely in warmer places. The results suggest that farmers tend to choose mixed crop-livestock farms and livestock-only farms in warmer locations while farmers choose crop-only farms in cooler locations. Surprisingly, farmers facing higher precipitation are mre likely to choose livestock-only farms and less likely to pick crop-only farms.

Soil types Acrisols, Kastanozems, Phaeozems, and Solonetz reduce the likelihood that crops are grown whereas Gleysols and Lithosols soils increase the probability of growing crops. Controlling for soils and climate, the Andean countries are more likely to engage in growing crops than the Southern Cone region. This may reflect regional differences in agricultural or land use policy or regional differences in the demand for meat (which may be higher in the Southern Cone countries). The coefficient for maize price is positive and very significant. Maize is a high valued crop. Farmers with higher maize prices are consequently more likely to choose crops-only. In contrast, the higher price of potatoes has a negative effect. In this case, potatoes are a low valued crop. If farmers are reduced to growing potatoes, they are more interested in livestock. The tomato price is negative for the mixed farms implying that mixing vegetables and livestock is not profitable.

The next analysis examines whether or not a farmer adopts irrigation, given that he has chosen to grow crops. In Table 4, we present two logit regressions of irrigation, one for farms with crops-only and one for farms with crops-livestock. Note that the coefficients for the two models are statistically different. The irrigation choice is not the same for crop-only and mixed farms. Ideally, we would have liked to have included the availability of water supplies and a measure of capital constraints. Unfortunately, neither variable was available.

There are many significant explanatory variables in the choice of irrigation equation for the crops-only farms. For example, summer precipitation and winter temperature are significant determinants of whether irrigation is chosen. In addition, the irrigation choice depends on soil types. Farms with soil type Acrisols are less likely to choose irrigation whereas farms with soil type Fluvisols are more likely to choose to irrigate. The soil variable used to identify the irrigation choice regression, clay texture, is negative but not significant in the crop-only regression. The selection terms were not significant implying there is no sample selection bias.

The results for the crop-livestock sample in Table 4 are quite different from the crop-only results. Summer precipitation is larger and more significant and both winter temperature and precipitation are significant. Only soil type Fluvisols had a positive and significant coefficient. The identifying variable, texture clay, is negative and significant as expected. Clay is difficult for irrigation because it leads to water logged fields. The selection terms are again insignificant implying there is no selection bias problem in the irrigation equations.

Looking at the marginal effects of annual climate on irrigation in Table 5, we see that farms in warmer locations are much less likely to choose irrigation. Although irrigation allows crops to survive higher temperatures, the relative profitability of irrigation falls as temperatures increase. Consequently, farmers are more likely to irrigate in cooler places. Farmers in locations with more rainfall are also less likely to irrigate. The marginal contribution of irrigation to net revenue (compared to dryland farming) falls as precipitation increases. Farmers do not need irrigation in places with high precipitation.

The third stage of the model estimates the conditional net income for each farm type. There are five different farm types identified in Table 6: crop only dryland, crop only irrigated, crop-livestock dryland, crop-livestock irrigated, and livestock only. Summer temperature is significant in the two crop-only and livestock-only regressions. Winter temperature is significant in the livestock-only and mixed dryland farms. Summer precipitation is significant in all but the mixed dryland farms. Winter precipitation is significant only in the crop-only dryland and livestock-only regressions. In farms that grow crops, the temperature squared coefficients are all negative (except for an insignificant coefficient on winter temperature for crop-only irrigated farms) implying a hill-shaped relationship. However, for the livestock-only farms, the winter temperature squared coefficient is large and positive implying a U-shaped relationship. The summer precipitation squared coefficients are largely negative (except for mixed irrigated farms) implying a hill-shaped relationship. The winter precipitation squared coefficients are largely insignificant except for a positive value for crop-only farms and a negative value for livestock only farms. These results suggest that the marginal impact of temperature and precipitation will depend on the climate facing the individual farm and will vary across the sample.

Table 6 also reveals that soils play a unique role in the net income farmers earn from each farm type. For example, Acrisols significantly increase the value of irrigated crop-only farms but are insignificant in all other regressions. Cambisols also increase the value of irrigated crop-only farms but also livestock-only farms. In contrast, Luvisols only increase the value of crop-only dryland farms and Planosols increase the value of crop-only dryland farms but decrease the value of irrigated crop-only farms and mixed dryland farms. The Andean dummy shows that crop only and mixed dryland farms in the Southern Cone are generally more profitable. Finally the selection terms are insignificant which suggest that the net revenue regressions are not vulnerable to sample selection problems.

Table 7 presents the marginal effects and elasticities of annual temperature and precipitation. Crop-only farms in warmer locations have significantly lower net incomes. These results support the earlier observation that farmers tend to choose crops-only in cooler locations. The precipitation has a significant effect only on livestock-only farms. Livestock-only farms earn higher incomes in wetter locations. For the remainder of the farm types, the annual precipitation effects are mixed and insignificant.

The temperature elasticities in Table 7 indicate that livestock farms are the most sensitive to warmer temperatures. Latin American livestock operations depend heavily on beef cattle which tend to be heat sensitive, a result also found in African livestock management (Seo and Mendelsohn 2006). Dryland crop farms are also sensitive to heat as they tend to be located in warm places. Irrigated crop farms are less sensitive partially because they are in cooler locations and partially because the irrigation reduces their vulnerability. The mixed farms are insensitive to temperature partially because they have a great deal of substitution possibilities to compensate for heat.

Table 7 also reveals that the net income of livestock-only farms is very sensitive to precipitation with an elasticity of 3. Precipitation has very little effect on the net incomes of the other farm types. One should not infer from these results that precipitation has no effect on individual crops. Part of the reason precipitation is having such little effect is that farmers can switch from one type of crop to another as precipitation varies.

5. Climate Change Impacts Simulations

In this section, we explore what consequences the cross sectional results imply if climate changes in the future. There are caveats one must keep in mind to make such forecasts. First, we assume that comparing a cool farm to a warm farm today is the same as having a farm experience a cool climate today versus a warm climate in the future. If there are important missing variables in our analysis that are correlated with climate, the predictions will be biased. Second, we assume that other changes in future conditions will not affect our climate predictions. For example, changes in technological advances, growth, and land use will not alter climate impacts. In practice, these future changes are both likely to occur and likely to have an effect on climate impacts. Future analyses should take these changes into account, but this is beyond the scope of this paper. We consequently limit ourselves to examine the impact of climate change on the current agricultural system. Third, we assume that prices will not change in any of these future scenarios even if supply changes dramatically. Partially, this can be justified because prices are determined in a world market and regional changes are not a good predictor of global changes. However, if prices change, this will tend to reduce the welfare impacts predicted in this analysis. Fourth, the analysis does not consider carbon fertilization effects. The increase in carbon dioxide is expected to be beneficial to plants in general and to specific plants in particular. Carbon fertilization is not taken into account in these forecasts although it will clearly increase productivity.

In order to see what impact future climates might have on Latin American agriculture, we examine three climate scenarios generated by Atmospheric Oceanic General Circulation Models (AOGCM's). The three models we rely upon provide a broad array of outcomes from a mild wet scenario to a very hot and dry scenario. Specifically, the three models are the Parallel Climate Model (PCM) (Washington et al. 2000), the Center for Climate System Research (CCSR) (Emori et al. 1999), and the Canadian Climate Centre (CCC) (Boer et al. 2000). The climate projections of these three models for Latin America are presented in Table 8. The PCM is the mildest scenario with small amounts of warming, small increases in summer precipitation, and large increases in winter precipitation. The CCC is the harshest scenario with substantial warming and reductions in summer precipitation. The CCSR scenario lies between these other scenarios. Temperature increases steadily over this century across all three models. Precipitation increases and decreases over time in no apparent pattern.

For each climate scenario, we make two predictions. In one prediction, we assume that the decision to choose farm type and irrigation is exogenous and will not change. In the second prediction, we assume these choices are endogenous and will change with each climate scenario. That is, we predict how each climate scenario will change the probability each farmer will choose each farm type (using the coefficients in Tables 2) and the probability of adopting irrigation (using the coefficients in Tables 4). Combining these results with the changes in the conditional land values yields an expected change in the land value for each farm for both the exogenous and endogenous cases.

Table 9 shows the current distribution of farm types for the sample (the exogenous case) and how that distribution would change over time (the endogenous case) for each climate scenario. The substantial warming associated with CCC and CCSR would cause the number of crops-only farms to shrink as early as 2020. According to these two scenarios, this effect would get stronger over time so that by 2100, almost one fourth of the crops-only farms would be gone in the CCC scenario and one eighth of these farms would be gone according to the CCSR scenario. According to the CCC and CCSR scenarios, the crop-only farms would become crop-livestock farms and livestock only farms. .The PCM scenario, however, provides a different forecast of impacts. With the milder and wetter PCM scenario, livestock farms would diminish, and crop-livestock farms would replace them.

Table 10 shows how irrigation choices would change with warming. All the climate scenarios predict an increase in irrigation for crop-only farms and a decrease in irrigation for mixed farms but the changes are generally not significant.

Table 11 shows what happens to conditional land values for each farm type-irrigation possibility. According to the CCC scenario, the land value of all farm types except livestock-only will fall with warming. The effect is particularly severe for crop-only dryland farms whose land values fall by almost half by 2100. Crop-livestock farms are the only exception in the CCC scenarios and their land values increase by one third by 2100. The CCSR scenarios yield qualitatively similar results to the CCC scenarios but the magnitudes of the effects are about half the size and consequently less significant. The results for the PCM scenarios, however, are quite different. The land values of crop-only dryland farms increase in the PCM scenario while net revenues in all other farm types fall. These PCM predictions, however, are not significantly different from zero.

Combining the results from Tables 9, 10, and 11, the overall expected climate impact on the value of farms is calculated in Table 12. The expected value of future climate scenarios for the exogenous approach uses the current probabilities of each farm type and irrigation with the future conditional land values. The difference between the future predicted land value and current expected land value is the welfare effect of climate change.

The baseline expected value of a farm in the sample is about $3400/ha.

Examining the endogenous predictions first, the expected value of a Latin American farm steadily falls over time with the CCC scenario until by 2100, the expected value falls by 28%. With the CCSR scenario, expected values also fall but the magnitude of the effect is smaller (19% by 2100). Finally, with the PCM scenario, the expected value initially increases by 10% by 2020, then fall back to current values. The milder wetter scenario predicted by the PCM model has little impact on Latin American farmers overall.

Table 12 also displays the 95% confidence interval around these final results. These were computed using bootstrapping with 200 draws. The PCM results are initially significant in 2020 and then become insignificant. The CCC results are not quite significant at first but become so by 2060. The CCSR results are only significant in 2100.

Finally, Table 12 provides the results for models that treat choice as exogenous versus endogenous. The exogenous model predicts larger damages and smaller benefits than the endogenous model in all scenarios. The magnitude of the difference increases with time. Capturing each farmer's ability to adapt to climate change by adopting different farm types and irrigation reduces the vulnerability in agriculture. The gap between the endogenous model and exogenous model is especially large in the CCC scenario.

6. Conclusion

This study expands on empirical agricultural models of irrigation choice to examine how such choices are influenced by climate. The paper models the choice of whether to grow crops, own livestock, and install irrigation and tests whether these choices are influenced by temperature and precipitation. The purpose of the model is to quantify some of the adaptations that farmers make to adjust to climate. Using cross sectional evidence, the paper models how Latin American farmers have adapted to the range of climates across the continent. Surveys of over 2000 farmers provided detailed information about crops, livestock and irrigation choices. Relying on a three stage integrated model of a farm, the choice of farm type, irrigation, and conditional land value were all calculated.

The results show that the choice of farm type and irrigation are very sensitive to climate. Farmers are more likely to pick crops-only in cooler temperatures whereas they will choose livestock in dryer locations. Farmers are more likely to choose a crop-livestock combination in hot locations. Farmers will tend to irrigate in locations that are both cool and dry. Of course, irrigation also requires access to water sources.

Conditional land values are also dependent on climate. Cooler than average temperatures increase land values for all farm types except irrigated crop-livestock farms. Increased precipitation raises land values for all farm types. However, the net revenues of some farm types respond more to cooler and wetter conditions than others. The net revenues of livestock farms are especially sensitive to both temperature and precipitation. The net revenues of dryland crop-only farms are very sensitive to cooler temperatures.

Applying these cross sectional results to future climate scenarios reveals some interesting outcomes. If the future climate scenario is very hot and dry, expected land values will fall by a third by 2100. Dryland crop-only farming will be especially hard hit and the amount of irrigation will fall substantially. Crop-livestock operations will be hurt but less so. If the scenario is hot and dry but not as severe, the impacts will have the same qualitative direction but the magnitude of the effect will be much smaller.

However, if the scenario is mild warming and wetter conditions, crop-only farms will increase in value and overall farm value will rise. Only livestock will be reduced in the future. The impacts of climate change consequently depend a great deal on the climate scenario.

The overall results suggest that farmers will do a great deal of adaptation in response to climate change. The results indicate that they will change whether they grow and own livestock and whether or not they will rely on irrigation. The exogenous model predicts higher damages and smaller benefits than the endogenous model. The gap between the models increases over time due to the increasing adaptive behavior and increasing climate impacts over the long term. These adaptive decisions which have been assumed to be exogenous in a great deal of the climate impact literature must be treated endogenously.

There are a number of caveats that must be kept in mind in interpreting these results. First, there was no information about water resources in the analysis and so this important variable was omitted. Second, the effect of carbon fertilization was not captured in the analysis since all the farms in the sample were exposed to the same level of carbon dioxide. Carbon fertilization is likely to improve future crop productivity and thus may offset some of the harmful effects predicted in this analysis. Third, the influence of technical change is not captured in this study. Future productivity increases may also offset some of the losses predicted in this analysis. Further, technological advances in crop breeding could create future crops that are more heat tolerant. Such possible effects are not considered. Fourth, the paper assumes that commodity and labor prices would not change with climate. If prices do change, the welfare impacts will be smaller. Finally, the analysis assumes that farmers in the future will be able to adapt as readily as farmers in the present. That is, the study assumes that the adaptations one currently sees from place to place can be done across time as climate change unfolds. All of these factors should be considered when projecting the future outcomes of climate change.

References

Adams, R., M., McCarl, B., A., Segerson, K., Rosenzweig, C., Bryant, K., Dixon, B., Conner, R., Evenson, R., Ojima, D. (1999), "The economic effects of climate change on US agriculture." in Mendelsohn and Neumann (*eds*.), *The Impact of Climate Change on the United States Economy*, Cambridge University Press; Cambridge, UK.

Adams, R.M., McCarl, B. 2001, "Agriculture: Agronomic-Economic Analysis" in Mendelsohn (ed) *Global Warming and the American Economy: A Regional Analysis*, Edward Elgar Publishing, UK.

Boer, G., G. Flato, and D. Ramsden. 2000. "A transient climate change simulation with greenhouse gas and aerosol forcing: projected climate for the 21st century", *Climate Dynamics* **16**, 427-450.

Caswell, Margiarette and David Zilberman. 1986. "The Effect of Well Depth and Land Quality On the Choice of Irrigation Technology." *American J. of Agricultural Economics* 68: 798-11.

Conde, C., D. Liverman, M. Flores, R. Ferrer, R. Araujo, E. Betancourt, G. Villareal, and C. Gay. 1997. "Vulnerability of Rainfed Maize Crops in Mexico to Climate Change", *Climate Research* 9:1-23.

De Siqueira, O.J.F., J.R.B. Farias, and L.M.A. Sans. 1994. "Potential Effects of Global Climate Change for Brazilian Agriculture: Applied Simulation Studies for Wheat, Maize, and Soybeans", in Rosenzweig, C. and A. Iglesias, eds*., Implications of Climate Change for International Agriculture: Crop Modeling Study*, U.S. EPA, Washington, DC, USA.

Dinar, Ariel and Dan Yaron. 1990. "Influence of Quality and Scarcity of Inputs on the Adoption of Modern Irrigation Technologies." *Western J. of Agricultural Economics* 15(2): 224-33.

Dinar, Ariel and David Zilberman. 1991. "The Economics of Resource-Conservation, Pollution-Reduction Technology Selection, The Case of Irrigation Water." *Resources and Energy* 13: 323-48.

Dinar, Ariel, Mark B. Campbell, and D. Zilberman. 1992. "Adoption of Improved Irrigation and Drainage Reduction Technologies Under Limiting Environmental Conditions." *Environmental & Resource Economics* 2: 373-98.

Downing, T. E. 1992. *Climate Change and Vulnerable Places: Global Food Security and Country Studies in Zimbabwe, Kenya, Senegal, and Chile,* Research Report No. 1, Environmental Change Unit, University of Oxford, Oxford, UK.

Emori, S. T. Nozawa, A. Abe-Ouchi, A. Namaguti, and M. Kimoto. 1999. "Coupled Ocean-Atmospheric Model Experiments of Future Climate Change with an Explicit Representation of Sulfate Aerosol Scattering", *J. Meteorological Society Japan* **77**: 1299-1307.

Heckman, J. 1979. "Sample Selection Bias as a Specification Error", *Econometrica* 47, 153-161.

Hofstadter, R., M. Bidegain, W. Baetghen, C. Petraglia, J.H. Morfinao, A. Califra, A. Hareau, R. Romero, J. Sauchik, R. Mendez, and A. Roel. 1997. Agriculture Sector Assessment, in *Assessment of Climate Change Impacts in Uruguay*, Montevideo, Uruguay.

Kurukulasuriya, P. and R. Mendelsohn. 2006a. “A Ricardian Analysis of The Impact of Climate Change on African Cropland” World Bank Research Policy Working Paper (forthcoming).

Kurukulasuriya, P. and R. Mendelsohn. 2006b. “Modeling Endogenous Irrigation:

The Impact Of Climate Change On Farmers In Africa”. World Bank Research Policy Working Paper (forthcoming)

Magrin, G., M. Travasso, R. Diaz, and R. Rodriguez. 1997. “Vulnerability of the agricultural systems of Argentina to climate change”, *Climatic Research* **9:** 31-36.

McCarthy, J., O. Canziani, N. Leary, D. Dokken, and K. White (eds.). 2001. *Climate Change 2001: Impacts, Adaptation, and Vulnerability*, Intergovernmental Panel on Climate Change Cambridge University Press: Cambridge.

Mendelsohn, R., W. Nordhaus and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis", *American Economic Review* 84: 753-771.

Mendelsohn, R. and A. Dinar. 1999. “Climate Change Impacts on Developing Country Agriculture” *World Bank Research Observer* 14: 277-293.

Mendelsohn, R., A. Dinar and A. Sanghi. 2001. "The Effect of Development on the Climate Sensitivity of Agriculture", *Environment and Development Economics* **6**: 85-101.

Mendelsohn, R., A. Dinar, and L. Williams. 2006a. “The Distributional Impact of Climate Change On Rich and Poor Countries” *Environment and Development Economics* **11**: 1-20.

Mendelsohn, R., A. Basist, F. Kogan, and P. Kurukulasuriya. 2006b. "Measuring Climate Change Impacts with Satellite versus Weather Station Data", *Climatic Change* (forthcoming).

Negri, D. H. and D. H. Brooks. 1990. "Determinants of Irrigation Technology Choice." *Western Journal of Agricultural Economics* 15: 213-23.

Reilly, J., et al. 1996. "Agriculture in a Changing Climate: Impacts and Adaptations." In IPCC (Intergovernmental Panel on Climate Change), Watson, R., M. Zinyowera, R. Moss, and D. Dokken, eds., *Climate Change 1995: Impacts, Adaptations, and Mitigation of Climate Change: Scientific-Technical Analyses*, Cambridge University Press: Cambridge.

Ricardo, D. 1817. "On the Principles of Political Economy and Taxation", John Murray, London.

Rosenzweig, C., and D. Hillel. 1998. *Climate Change and the Global Harvest: Potential Impacts of the Greenhouse Effect on Agriculture* Oxford University Press, New York.

Seo, N. S., R. Mendelsohn, and M. Munasinghe. 2005. "Climate Change and Agriculture in Sri Lanka: A Ricardian Valuation", *Environment and Development Economics* 10: 581-596.

Seo, N. S., and R. Mendelsohn. 2006. "The Impact of Climate Change on Livestock Management in Africa: A Structural Ricardian Analysis", World Bank Research Policy Working Paper, Washington D.C..

Singh, I., L. Squire, and J. Strauss. 1986. "A Survey of Agricultural Household Models:

Recent Findings and Policy Implications”, *World Bank Economic Review* 1: 149-179.

Washington, W., et al. 2000. “Parallel Climate Model (PCM): Control and Transient Scenarios”. *Climate Dynamics* 16: 755-774.

Table 1: Number of Farms of Each Type

	Dryland	Irrigated	All
Crop Only	360	277	637
Crop and Livestock	948	179	1127
Livestock Only	268	1	269
All	1576	457	2003

Table 2: Multinomial Logit Model of Farm Type Selection

	Crops Only		Both Crops and Livestock	
Var.	Est.	Chi-sq	Est.	Chi-sq
Intercept	-1.939	0.74	-1.787	0.69
Summer Temperature	0.717	9.21	0.333	2.23
Summer Temperature^2	-0.038	34.79	-0.024	14.98
Summer Precipitation	-0.040	60.73	-0.029	34.02
Summer Precipitation^2	0.000	40.40	0.000	22.54
Winter Temperature	1.020	92.60	1.000	95.56
Winter Temperature^2	-0.015	25.04	-0.017	31.44
Winter Precipitation	-0.026	18.73	-0.022	13.72
Winter Precipitation^2	0.000	6.23	0.000	7.03
Soil Acrisols	-0.018	12.02	-0.018	15.61
Soil Gleysols	0.016	2.71	0.001	0.02
Soil Lithosols	0.008	2.48	0.008	2.43
Soil Kastanozems	-0.014	4.48	-0.005	0.71
Soil Phaeozems	-0.010	7.71	-0.013	13.46
Soil Solonetz	-0.016	5.10	-0.015	5.04
Maize Price	1.095	15.66	1.233	19.71
Potato Price	-21.434	56.30	-0.820	4.46
Tomato Price	-0.828	1.98	-5.031	20.43
Andean Dummy	2.460	81.49	2.105	62.06
Commercial Dummy	-0.025	0.06	-0.129	1.73

** denotes the statistics estimate is significant at the 1% level.

Table 3: Bootstrap Marginal Climate Effects on Farm Type Selections

	Crop Only	Crop and Livestock	Livestock Only
Baseline	27.5% (25.7%, 29.5%)	50.3% (48.6%, 53.2%)	22.4% (18.2%, 24.9%)
Temperature (C˚)	-1.6% (-2.0%, -0.9%	0.5% (0.0%, 1.3%	1.0% (0.2%, 1.5%)
Precipitation (mm/mo)	-0.13% (-0.15%, -0.07%)	0.01% (-0.02%, 0.07%)	0.11% (0.05%, 0.15%)

* Numbers in parentheses are 95% confidence intervals.

Table 4: Logit Model of Irrigation

	Crop Only Farms		Both Crop and Livestock Farms	
Var.	Est.	Chi-sq	Est.	Chi-sq
Intercept	2.411	1.67	0.654	0.24
Summer Temperature	0.021	0.01	0.058	0.11
Summer Temperature^2	-0.003	0.14	-0.002	0.08
Summer Precipitation	-0.011	6.06	-0.020	21.54
Summer Precipitation^2	0.000	0.65	0.000	13.11
Winter Temperature	-0.274	6.24	0.143	2.91
Winter Temperature^2	0.011	9.97	-0.006	5.40
Winter Precipitation	-0.006	2.34	-0.010	6.72
Winter Precipitation^2	0.000	0.08	0.000	0.85
Soil Acrisols	-0.023	6.40	-0.009	1.45
Soil Cambisols	-0.019	2.59	-0.002	0.06
Soil Ferralsols	-0.005	1.11	-0.001	0.07
Soil Gleysols	-0.014	1.48	0.014	2.85
Soil Fluvisols	0.025	13.30	0.025	17.91
Texture Clay	-0.303	1.57	-0.485	4.60
Andean dummy	0.139	0.12	-0.850	6.82
Selection mixed	-0.552	1.69		
Selection livestock	0.138	0.26		
Selection crops			-0.260	0.30
Selection livestock			0.670	2.71

** denotes the estimate is significant at1% level and * at 5% level.

Table 5: Bootstrap Marginal Effects on Irrigation Choice

	Crop Only	Both Crop and Livestock
Baseline Prob.	46.2% (40.8%, 49.4%)	19.8% (17.5%, 21.9%)
Marginal Temp Effects	-0.6% (-2.9%, 0.9%)	-0.5% (-1.3%, -0.2%)
Marginal Prec Effects	-0.2% (-0.3%, -0.1%)	-0.2% (-0.2%, -0.1%)

* Numbers in parentheses are 95% confidence intervals.

Table 6: Conditional Ricardian Model

	Crop Only Dryland		Crop Only Irrigated		Livestock Only	
Var.	Est.	T-stat.	Est.	T-stat.	Est.	T-stat.
Intercept	-3331.45	-0.81	-2275.49	-1.05	-5970.85	-2.90
Summer Temperature	439.59	1.61	729.83	2.74	427.52	2.03
Summer Temperature^2	-16.80	-2.14	-18.81	-2.27	-3.13	-0.58
Winter Temperature	340.28	1.61	-322.90	-1.34	-745.58	-6.80
Winter Temperature^2	-11.39	-1.59	5.50	0.68	16.97	6.82
Summer Precipitation	19.41	2.66	34.34	3.08	52.24	6.80
Summer Precipitation^2	-0.03	-2.38	-0.07	-2.33	-0.16	-6.04
Winter Precipitation	-11.85	-2.81	16.10	1.43	9.33	3.44
Winter Precipitation^2	0.04	2.48	-0.06	-1.09	-0.05	-3.75
Soil Acrisols	14.12	1.41	94.95	2.22	2.92	0.97
Soil Cambisols	2.05	0.16	57.86	1.54	27.65	4.36
Soil Gleysols	-9.51	-0.90	21.98	0.70	4.16	1.22
Soil Phaeozems	-16.04	-1.12	-30.84	-2.80		
Soil Kastanozems	2.29	0.23	-4.58	-0.48	2.06	0.75
Soil Luvisols	18.06	2.13	8.82	0.99		
Soil Planozols	11.70	2.58	-1830.86	-2.73	2.97	1.50
Andean dummy	-2940.12	-6.03	996.55	1.04	-669.79	-1.01
Selection irrigation	-321.22	-0.41				
Selection dryland			-2275.49	-1.05		
Selection crop					-739.20	-1.70
Selection crop/livestock					9.58	0.02
Adjusted R-sq		0.28		0.19		0.41

** denotes the estimate is significant at 1% level and * at 5% level.

Table 6: Conditional Ricardian Model: Continued

	Mixed Non-Irrigated		Mixed Irrigated	
Var.	Est.	T-stat.	Est.	T-stat.
Intercept	-1091.42	-0.98	-847.00	-0.46
Summer Temperature	82.26	0.66	245.37	1.16
Summer Temperature^2	-2.13	-0.58	-5.01	-0.76
Winter Temperature	352.23	5.70	54.59	0.35
Winter Temperature^2	-12.45	-6.75	-4.05	-0.89
Summer Precipitation	5.97	1.70	-12.54	-1.18
Summer Precipitation^2	-0.01	-1.17	0.05	2.27
Winter Precipitation	-0.10	-0.04	-2.59	-0.33
Winter Precipitation^2	0.00	-0.31	-0.03	-0.86
Soil Acrisols	-3.17	-0.85	2.20	0.21
Soil Cambisols	-2.29	-0.51	4.39	0.52
Soil Gleysols	-6.53	-1.04	-0.06	0.00
Soil Fluvisols	-1.00	-0.09	3.75	0.49
Soil Kastanozems	1.12	0.19	-11.79	-0.40
Soil Luvisols	2.47	0.74	-6.54	-1.02
Soil Planosols	-5.43	-2.26	-1.84	-0.40
Andean dummy	-1373.39	-5.33	-728.35	-1.31
Selection irrigation	665.19	1.47		
Selection dryland			-243.93	-0.64
Selection crop				
Selection crop/livestock				
Adjusted R-sq		0.21		0.34

** denotes the estimate is significant at`1% level and * at 5% level.

Table 7: Bootstrap Marginal Climate Effects and Elasticities on Conditional Income

Farm Type	Temperature	Precipitation	Temperature	Precipitation
	Marginal Effects		Elasticities	
	-188	0	-1.59	0.03
Dryland Crop Only	(-314, -92)	(-10, 5)	(-2.71, -0.95)	(-0.69, 1.11)
	-210	21	-1.05	0.65
Irrigated Crop Only	(-346, -35)	(-13, 62)	(-1.88, -0.18)	(-0.39, 1.61)
	-5	4	-0.06	0.36
Crop/livestock Dryland	(-80, 49)	(-7, 9)	(-1.09, 0.69)	(-0.78, 0.95)
	-24	-7	-0.28	-0.46
Crop/livestock Irrigated	(-38, 93)	(-38, 11)	(-0.44, 1.21)	(-2.93, 0.66)
	-61	15	-1.90	2.98
Livestock Only	(-122, 67)	(4, 23)	(-4.41, 1.91)	(1.09, 4.41)

* Numbers in parentheses are 95% confidence intervals.

* Climate elasticities (% change in net revenue per percentage change in climate variable) are in parenthesis.

Table 8: AOGCM Climate Scenarios

	NOW	2020	2060	2100
Temperature Summer (˚C)				
CCC	19.9	+1.5	+2.8	+5.0
CCSR	19.9	+1.2	+2.1	+3.1
PCM	19.9	-0.1	+0.7	+1.4
Temperature Winter (˚C)				
CCC	16.4	+1.3	+2.6	+5.2
CCSR	16.4	+1.4	+2.3	+3.2
PCM	16.4	+1.2	+1.9	+2.6
Precipitation Summer (mm/mo)				
CCC	162	-2.5%	-11.7%	-12.3%
CCSR	162	+1.9%	+2.5%	-2.5%
PCM	162	-3.1%	+2.5%	+1.9%
Precipitation Winter (mm/mo)				
CCC	75	-2.7%	-5.3%	+1.3%
CCSR	75	+1.3%	-4.0%	-6.7%
PCM	75	+32.0%	+32.0%	+22.7%

Table 9: Bootstrap Probabilities of Each Farm Type with Climate Change

	Crop Only	Crop- Livestock	Livestock Only
Baseline	63.1% (51.1%, 77.3%)	27.0% (11%, 43%)	7.9% (2.9%, 12.9%)
2020			
CCC	-6.3% (-7.5%, -5.1%)	+2.9% (0.9%, 4.9%)	+3.3% (1.7%, 4.9%)
CCSR	-5.0% (-6.2%, -3.8%)	+2.3% (2.1%, 2.5%)	+2.7% (2.5%, 3.2%)
PCM	2.4% (-0.4%, 6.2%)	+2.0% (-0.2%, 4.2%)	-4.7% (-7.9%, -1.5%)
2060			
CCC	-11.4% (-14.6%, -8.2%)	+6.1% (0.9%, 11.3%)	+4.7% (4.0%, 8.7%)
CCSR	-7.0% (-9.6%, -5.4%)	+4.7% (1.5%, 7.9%)	+2.2% (0.2%, 4.2%)
PCM	-1.1% (-4.3%, 2.1%)	+4.1% (1.3%, 6.9%)	-2.7% (-4.9%, -0.5%)
2100			
CCC	-23.1% (-29.2%, -17.1%)	+7.5% (-2.5%, 18.2%)	+13.7% (3.7%, 23.4%)
CCSR	-12.7% (-17.1%, -8.3%)	+6.5% (1.3%, 11.7%)	+5.4% (0.6%, 10.2%)
PCM	-2.1% (-5.5%, 1.3%)	+5.3% (2.5%, 8.3%)	-2.8% (-4.8%, -0.8%)

*Calculated from coefficients in Table 2.

* Numbers in parentheses are 95% confidence intervals.

Table 10: Bootstrap Irrigation Probabilities with Climate Change

	Now	2020	2060	2100
Crop Only				
CCC	32.6% (13.3%, 51.6%)	+1.4% (-2.8%, 5.6%)	+4.5% (-4.3%, 9.1%)	+8.0% (-8.4%, 16.2%)
CCSR	32.6% (13.3%, 51.6%)	+1.3% (-1.9%, 4.5%)	+2.7% (-2.9%, 5.6%)	+3.8% (-8.4%, 13.0%)
PCM	32.6% (13.3%, 51.6%)	+1.8% (-1.8%, 5.4%)	+1.8% (-1.2%, 3.2%)	+3.0% (-0.4%, 6.4%)
Crop and Livestock				
CCC	23.5% (9.5%. 37.6%)	-1.3% (-2.7%, 0.1%)	-2.2% (-4.4%, 0.0%)	-5.5% (-11.1%, 1.1%)
CCSR	23.5% (9.5%. 37.6%)	-2.1% (-3.5%, -0.7%)	-2.2% (-4.2%, -0.2%)	-2.6% (-5.8%, 0.6%)
PCM	23.5% (9.5%. 37.6%)	-2.6% (-5.3%, 0.0%)	-3.4% (-6.2%, -0.6%)	-2.8% (-5.0%, -0.6%)

*Calculated from coefficients in Table 4.

* Numbers in parentheses are 95% confidence intervals.

Table 11: Bootstrap Impact of Climate Change on Conditional Land Values

	Crop Only Dryland	Crop Only Irrigated	Crop-Livestock Dryland	Crop-Livestock Irrigated	Livestock Only
Baseline	4312 (469, 7734)	4443 (1409, 7493)	2325 (1185, 3390)	2832 (1409, 4233)	2083 (985, 3178)
2020					
CCC	-408 (-668, -142)	-201 (-525, 80)	-104 (-206, -2)	-198 (-518, 120)	+152 (-148, 454)
CCSR	-342 (-565, -122)	-125 (-384, 104)	-121 (-223, -19)	-119 (-369, 141)	+106 (-94, 307)
PCM	+661 (-260, 1465)	-248 (-491, 159)	-102 (-222, 18)	-441 (-1201, 339)	-310 (-733, 116)
2060					
CCC	-927 (-1535, -326)	-409 (-1369, 564)	-277 (-477, -77)	-426 (-673, 128)	+327 (-324, 933)
CCSR	-585 (-925, -245)	-219 (-876, 459)	-214 (354, -73)	-21 (-262, 229)	+216 (-126, 556)
PCM	+457 (-357, 1145)	-291 (-523, 138)	-136 (-273, 2)	-379 (-766, -3)	-274 (-624, 86)
2100					
CCC	-1919 (-3349, -508)	-931 (-2190, 1212)	-650 (-1060, -240)	-582 (-1084, -80)	+740 (-265, 1890)
CCSR	-1057 (-1756, -355)	-516 (-1142, 538)	-334 (-556, -112)	-117 (-597, 365)	+403 (-97, 907)
PCM	+365 (-145, 1155)	-348 (-745, 288)	-204 (-345, -73)	-317 (-743, 121)	-231 (-644, 169)

*Calculated from coefficients in Table 6.

* Numbers in parentheses are 95% confidence intervals.

Table 12: Climate Change Impacts on Expected Land Value

	Exogenous Impact ($/ha)	Endogenous Impact ($/ha)	Exogenous % change	Endogenous % change
Baseline	3412	3412		
2020				
CCC	-237 (-480, -1)	-185 (-750 to 32)	-6.9%	-5.4%
CCSR	-196 (-397, -2)	-143 (-563 to 45)	-5.7%	-4.2%
PCM	159 (-392, 695)	+332 (4 to 868)	4.7%	9.7%
2060				
CCC	-538 (-1101, 41)	-463 (-1465 to -26)	-15.8%	-13.6%
CCSR	-323 (-527, 32)	-350 (-868 to 34)	-9.5%	-10.3%
PCM	58 (-414, 525)	+80 (-133 to 378)	1.8%	2.3%
2100				
CCC	-1122 (-2185, 129)	-957 (-2460 to -98)	-32.9%	-28.0%
CCSR	-601 (-1143, 30)	-648 (-1473 to -63)	-17.6%	-19.0%
PCM	1 (-383, 525)	-36 (-316 to 517)	0.1%	-1.1%

95% confidence intervals are in parentheses. They were estimated using 200 bootstrap repetitions.

Figure 1: Ricardian Model of Net Income and Precipitation