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THE ECONOMIC IMPACTS OF CLIMATE CHANGE: EVIDENCE FROM AGRICULTURE

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This dissertation is dedicated to my father and mother

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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ABSTRACT

In this paper, I analyze the economic impacts of climate change on agriculture as well as the adaptation possibilities of farmers. In my first chapter, I estimate the impact of climate change on agricultural land values using a variety of methods and forecast models. First, I combine a framework that incorporates different possible forecasts of future climate with degree days, a temperature measure that allows to capture the effects of extreme temperatures. I use this framework to estimate the damages of climate change relative to a constant 2002 climate. Second, I exploit climate variation over time between 1978 and 2002 within counties to estimate a land value regression. Using this variation, I can address the time-invariant omitted-variable bias of a cross-sectional regression. Furthermore, I estimate the impacts using a range of climate models. The present discounted damages range from \$22 to \$204 billion in 2002 dollars, with a mean of \$67 billion dollars using a discount rate of 5 percent. In the models that use climate variation within counties over time, I find that estimated damages are on average \$64 billion larger than the cross-sectional regressions. Furthermore, the choice of climate model has significant economic importance as the estimates across climate models vary by about \$160 billion for nearly all specifications. Finally, I document substantial heterogeneity in impacts across counties. In the second chapter, Michael Greenstone, Ishan Nath, and I investigate how much farmers can adapt to climate change through their choice of crops. By combining a discrete choice framework with data on insurance costs for farmers, we estimate the impact of predicted changes in climate on farmer profits relative to other uses of land. In all specifications, climate change will produce a severe reduction in the share of land used to grow corn and soybeans in the US by the middle of the century. Farmers who grow corn would gain between 1.4 and 2.5 cents for an additional growing degree day relative to the outside option. On the other hand, farmers would lose between 17.9 and 32.3 cents from an increase in a growing degree day above 29 °C. We find similar results for soybeans. These results are robust across census years and choice sets. When farmers are allowed to re-optimize their land use, climate damages in 2050 are \$8.9 to

\$11.8 billion lower compared to a scenario where their crop choice in 2002 is held constant.

CHAPTER 1

THE ECONOMIC IMPACTS OF CLIMATE CHANGE: EVIDENCE FROM LAND VALUES IN AGRICULTURE

1.1 Introduction

A growing body of research has demonstrated that our climate is changing (Meehl et al. 2007). While the impact of climate change affects many areas, one area that is most susceptible to climate change is agriculture due to its inherent dependence on climate. This dependence has led to a large body of literature (for a review, see Dell, Jones and Olken 2014; Carleton and Hsiang 2016). Yet estimating the relationship between climate and economic impacts is challenging. While estimates of the impacts on single crops have been well-documented, they overestimate the impacts of climate change as they do not allow farmers to substitute among different crops, production practices, or uses of land (Mendelsohn, Nordhaus, and Shaw 1994).

On the other hand, research that has tried to incorporate the full extent of substitution possibilities using land values has faced its own limitations. This type of research has attempted to estimate the relationship between land values and climate in a cross-sectional regression. However, this approach has been challenged for its instability and potential omitted variable bias (Deschênes and Greenstone 2012). In addition, the literature so far has implicitly assumed that farmers never predict increases in temperatures, an assumption that has become increasingly questionable as awareness of climate change has increased (Severen, Costello and Deschênes 2016, SCD henceforth). Finally, Burke et al. (2015) point out that most of these papers only use one or two climate models, severely underestimating the range of damages that can arise from differences in climate model predictions.

In this paper, I address these limitations by estimating the impact of climate change on agricultural land values using a variety of methods and forecast models. First, I combine a framework that incorporates different farmer forecasts of future climate, developed by SCD, with degree days, which is a temperature measure that captures the impacts of extreme temperatures. Second, I use this framework to estimate the present discounted damages of climate change relative to a constant 2002 climate. Third, I exploit climate variation over time between 1978 and 2002 within counties to estimate a land value regression. Using this variation, I can address the potential time-invariant omitted-variable bias of a cross-sectional regression. Fourth, I use climate models that were used in the Intergovernmental Panel on Climate Change's (IPCC henceforth) assessment of the state of the science (Nakicenovic 2000). Using these models, I can investigate the range of impacts across climate models, instead of relying on any specific climate model (Burke et al. 2015)..

I find that the present discounted damages with a 5 percent discount rate range from $22 to $204 billion in 2002 dollars across specifications. The mean damage is $67 billion dollars. In addition, the damages using the long-run climate variation are about $64 billion larger than the cross-sectional regressions, suggesting a downward bias on damages in the cross-sectional regression. Furthermore, the choice of climate model is of significant economic importance as the estimates across climate models vary about $160 billion for nearly all specifications. Finally, I document substantial heterogeneity in impacts across counties.

In comparison, these results are much smaller than the estimates of SCD's main specification, who find estimated damages of -$711 billion to -$998.6 billion for a sample of 2,112 counties with a discount rate of three percent.[1] On the other hand, my results are much closer to one of their sensitivity checks where they use ten temperature bins instead of monthly averages. With these temperature bins, they find damages from -$58 to -$160 billion.[2] Furthermore, similar to SCD, I find a similar effect that the coefficients on the climate variables are biased downwards. On the other hand, the coefficient on beneficial temperatures is biased downwards relatively more than those of harmful temperatures. The combined impact thus leads to an overestimation of climate damages, which is in contrast to

1. Another difference is that they calculate damages from 2007 to 2099 and convert them to 2005 dollars.

2. They report damages of $47 to $128 billion, but I have rescaled them to get comparable damage calculations.

SCD who find that damages are biased downwards. My damages are also in the same range as Deschênes and Greenstone (2007), who report damages from $66 billion to $163 billion.[3]

Throughout this paper, I provide present discounted value estimates of the impact of climate change on agriculture in contrast to the literature which compares steady state levels. In the literature, the majority of the papers compare steady state levels around the middle or the end of the century, relative to a benchmark period. While these estimates are highly valuable for comparing estimates of climate change, ultimately climate policy has to rely on the change in total discounted impacts.[4] Although I analyze steady state levels as well, I address this shortcoming by presenting discounted value impacts in this paper. I build upon a framework by SCD to estimate the present discounted value of any two climate paths. I estimate the present discounted impacts of climate change relative to a constant 2002 climate. I do a robustness check as I compare steady state levels of 2050 relative to 2002 and find similar impacts as Schlenker, Haneman and Fisher (2006) (SHF henceforth).

In addition, the literature on land values has used a single forecasting model for farmers, which assumes that farmers predict that future climate will be exactly that of the present. While this assumption was reasonable in the 1980s and 1990s, this assumption becomes increasingly hard to maintain. Using the framework from SCD, I can accommodate different forecasts of farmers. I allow for a combination of farmer forecasts of a model that predicts no changes in climate and a forecast model that predicts changes according to climate model projections. By exploring the convex combination of these two forecast models, farmers can have a range of predictions of climate change. I combine these forecasts with a temperature variable, called "degree days". These degree days allow me to capture crop sensitivity to cumulative exposure to extreme temperatures. This cumulative exposure to extreme

3. My cross-sectional results provide smaller estimates than their damages, which is expected given the adaptation possibilities over the long-run that are captured within the land value framework.

4. As the challenge of climate change is fundamentally one of externalities, the standard solution is to use carbon tax or cap-and-trade equal to the social cost of carbon (Becker, Murphy and Topel 2011). And this social cost of carbon includes the social cost of carbon on agriculture. Any climate policy that is based on a cost-benefit analysis has to incorporate estimates of the potential benefits of climate mitigation on agriculture.

temperatures has been found to be a strong predictor of crop yields (Schlenker and Roberts 2009; Burke and Emerick 2016).

Furthermore, I address a long-standing tension in the literature as I exploit differences in climate variation over time between 1978 and 2002 by county to estimate a regression with land values. Historically, researchers have developed several approaches to analyze impacts of climate change (Aufhammer and Schlenker 2014). However, most of these approaches fall into what Mendelsohn, Nordhaus, and Shaw (1994) (MNS henceforth) call the "production-function" approach. These approaches predominantly analyze the impact of climate in one specific area and often one crop. MNS argue that this approach assumes a "dumb-farmer" scenario, as farmers are very limited in how they can respond to changes in climate. Consequently, these approaches will obtain results that will overestimate the true impact of climate change.

As a reaction, MNS developed the "ricardian approach" based on land values. They proposed to estimate the relationship between climate and land values, suitably controlling for soil and socio-economic factors. This relationship will then enable the researcher to use predicted changes in climate to estimate the impact on land values. This approach provides one of the most powerful and theoretically appealing approaches because land values represent the present value of all future profits of the land. In addition, land values incorporate all possible uses of land and the full set of current technologies. As a result, if a researcher can establish the impact of climate change on land values, then the damages due to changes in the climate can be calculated. These damages will then reflect the full set of adaptation possibilities. In their paper, MNS develop a model of land prices as a function of climate and non-climate variables.[5] Many papers have followed in their footsteps by using different variations of this methodology (for a review, see De Salvo et al. 2014).

However, DG (2007) (DG henceforth) found that this analysis can be sensitive to the

5. After running their specification, MNS obtain estimates of how land values respond to differences in climate. With these estimates, they then simulate future land values with a climate model. This simulation allows them to calculate the damages (or benefits) of climate change.

regression specification and choice of census year. They therefore argued that there could be a potential omitted variable bias problem. To overcome this, DG proposed a panel-data approach, based on year-to-year weather fluctuations, which can overcome this potential problem. Furthermore, DG build on MNS by using profits as their measure to avoid the focus on single crops. Although DG used profits as their measure, this measure has been challenged on several grounds (Fisher et al. 2012). The subsequent literature therefore often has returned to focusing on single crops (for a review, see D'Agostino and Schlenker 2016) even though this approach was still subject to the limited adaptation criticism of MNS. Besides the limitations of the outcome value, DG also pointed out that year-to-year weather fluctuations could be a poor proxy for actual climate changes as these fluctuations do not allow farmers to use the full range of adaptation possibilities. Recent papers also have implemented augmented cross-sectional land value regressions to address these concerns in various ways. (Masetti and Mendelsohn 2015; Huang & Sim (2017) ; Ortiz-Bobea 2016; Fezzi and Bateman 2015).

In this paper, I overcome this tension as I combine climate differences over a thirty year time period while still using land values. As such, I can utilize county fixed effects that directly control for the unobserved time-invariant variables. I am therefore able to bridge most of the tension between the cross-section and the panel-data approach, with its predominant focus on single crops and year-to-year weather fluctuations. The idea of using climate variation over longer periods of time has been applied before to crops in Lobell and Asner (2003) and Burke and Emerick (2016). Burke and Emerick (2016) call this method of using changes in climate within a county over time a "long differences" approach. However, to the best of my knowledge, I am the first to use a land-value regression with county fixed effects to use long-term differences in climate within counties. The closest papers are Burke and Emerick (2016) and Ortiz-Bobea (2016). Burke and Emerick (2016) use a long differences approach but focus only on corn and soybean yields. Ortiz-Bobea (2016) uses district fixed effects in some specifications, which is a more granular level than by state, but still leave possible omitted variables unresolved on a county level. To address this, he proposes a different estimator based on a nearest-neighbor approach to solve the possible omitted variable bias problem. In contrast, I use county-fixed effects which capture all time-invariant omitted variable bias.

Besides these empirical specifications, I also analyze the impact of the choice of climate model. As Burke et al. (2015) demonstrate, climate models vary substantially in their predictions, based on emission scenarios and modeling assumptions. Burke et al. (2015) show this impact for the DG, MNS and Schlenker, Hanemann and Fisher (2005) papers. Therefore, using only one climate model will yield a severe under-estimation of the range of damages and uncertainty. To address this, I use 18 climate models used by the IPCC in their 2007 report. I demonstrate the substantial difference in predictions from these models. The choice of climate model leads to a consistent range of $200 billion in damages across specifications.

Section 1.2 sets up the theoretical framework, while I discuss the agricultural and climate data in section 1.3. Section 1.4 documents the econometric strategy, while section 1.5 discusses the results and discussion. Section 1.6 concludes.

1.2 Conceptual Framework for the Impacts of Climate Change on Agriculture

1.2.1 Land Values As the Present Discounted Value of All Future Rents

In this paper, I aim to estimate the relationship between climate and profitability while I allow for different climate forecasts of farmers. To do so, I set up a framework based on SCD, who show how different forecasts can be included into the empirical specification. The building block of this framework is that the price of land is the present discounted value of all the future rents R_t, whereby the rents are a function of the climate state $\mathbf{C}_t$ and other factors. While other factors influence land prices, I will focus my analysis in this section on climate variables.[6] With a discount rate of r, the price of land can be written as

$$P_t\left(\mathbf{C}_t,\, \mathbf{C}_{t+1},\, \ldots\right) = E_t\left(\sum_{\tau=t}^{\infty} R_{\tau-t}\left(\mathbf{C}_{\tau-t}\right)\left(\frac{1}{1+r}\right)^{\tau-t}\right). \tag{1.1}$$

I approximate the rent function in a given period by a linear function of the climate variable $\mathbf{C}_t$L:

$$R_t\left(\mathbf{C}_t\right) \approx a + \mathbf{b}_t\mathbf{C}_t. \tag{1.2}$$

where $\mathbf{b}_t$ is the impact of a change in $\mathbf{C}_t$ on the rent in that year. Besides the sensitivity to climate, this coefficient also reflects the technology at any time t. Yet the impact of future technology on this coefficient is not clear. On the one hand, future technology might decrease the climate sensitivity with the advent of more drought-resistant varieties. On the other hand, higher yielding varieties might be more sensitive to extreme temperatures, despite reaching a higher profit level.[7] As future technology is inherently unknown, I will assume a constant technology coefficient in this paper. However, it bears noting that the coefficient on climate will incorporate some of these technological evolutions. A further element of the coefficient vector $\mathbf{b}$ is based on the interactions and levels of climate as different levels of climate can lead the farmer to different existing technology choices or choice of crops. With this in mind, I can rewrite equation (1.1) with equation (1.2) which yields

$$P_t \approx E_t\left(\sum_{\tau=t}^{\infty}\left(a + \mathbf{b}\mathbf{C}_{\tau-t}\right)\left(\frac{1}{1+r}\right)^{\tau-t}\right). \tag{1.3}$$

Using the linearity of the expectations operator, this expression can be further simplified to

$$P_t \approx \left(\frac{1+r}{r}\right)a + \mathbf{b}E_t\left(\sum_{\tau=t}^{\infty}\mathbf{C}_{\tau-t}\left(\frac{1}{1+r}\right)^{\tau-t}\right). \tag{1.4}$$

6. In the empirical analysis, I control for these other factors in the regression. I elaborate further on this in section 1.4.

7. A level shift would be captured by a change in the constant.

Equation (1.4) shows that $E_t\left(\sum_{\tau=t}^{\infty}\mathbf{C}_{\tau-t}\left(\frac{1}{1+r}\right)^{\tau-t}\right)$, the expected present discounted value of climate, is the key empirical variable needed. Once I obtain an empirical estimate, I can estimate this land value regression, controlling for other factors.

To gain empirical traction on this key variable, I follow SCD and define different farmer forecast models. In the first forecast model, I use a "No Change" (NC) index $\mathbf{I}_t^{nc}$, whereby the farmer assumes that the climate $\mathbf{C}_t$ she observes at time t will be the climate for all future periods:

$$\mathbf{I}_t^{nc} \equiv \sum_{\tau=t}^{\infty}\mathbf{C}_t\left(\frac{1}{1+r}\right)^{\tau-t} \text{ (\textit{i.e.}, the \textit{No Change} index)}. \tag{1.5}$$

As a second forecast model, I utilize forecasts from the IPCC to construct a "Mean Change" (MC) index $\mathbf{I}_t^{mc}$. Using this forecast index, farmers utilize the state of the art modeling predictions at time t:

$$\mathbf{I}_t^{mc} \equiv \sum_{\tau=t}^{\infty}\mathbf{C}_{\tau-t}\left(\frac{1}{1+r}\right)^{\tau-t} \text{ (\textit{i.e.}, the \textit{Mean Change} index)}. \tag{1.6}$$

I will assume that the expectations of the farmer are a weighted combination of these two indices with weight ω_t. Thus I can approximate the expected present discounted value of climate which yields

$$E_t\left(\sum_{\tau=t}^{\infty}\mathbf{C}_{\tau-t}\left(\frac{1}{1+r}\right)^{\tau-t}\right) = \mathbf{I}_t = (1-\omega_t)\,\mathbf{I}_t^{nc} + \omega_t\mathbf{I}_t^{mc}. \tag{1.7}$$

In this formulation, I have assumed that farmers have a constant weight on the indices throughout the future at any given time t. Of course, as climate change becomes more pronounced or as farmers use different forecasting methods, these weights will differ across periods. In addition, a higher weight will lead to a stronger incorporation of predicted climate changes. Yet once the coefficients $\mathbf{b}$ are estimated, these coefficients can be used for the comparison between any two climate paths.

Ideally, the econometrician would know the forecast process of farmers, yet this is empirically hard to obtain. There are surveys on farmers believe about climate change, but the results are often hard to interpret. Rejesus (2012) reports the results of a survey of 315 farmers who grow corn, cotton, grain, sorghum, soybeans, rice or wheat in North-Carolina. He finds that 36.6 percent of farmers believe that climate change is scientifically proven. Among the farmers in the survey, 18.3 percent believes "that climate change will decrease average yields by 5% or more over the next 25 years." (Rejesus 2012, 4). There is also a report by the Iowa State Extension Service (2011), who collected 1,276 questionnaires of Iowa farmers. 68 percent of these farmers believe that climate change is occurring. Of those farmers, 45 percent believe that humans play a role in this changing climate, whereas 25 percent believes that they are not human-made. In the survey, 46 percent of farmers believe that extreme weather events will happen more frequently in the future. Interestingly, 33 percent of farmers believe that Climate change is not a big issue because human ingenuity will enable us to adapt to changes. This survey also documents the possible responses of farmers. Among farmers, 62 percent believes seed companies should develop crop varieties that are adapted to new climate situations and 61 percent believes that farmers themselves should take steps to protect their land from increased precipitation. While more research needs to be done to understand how farmers make their forecasts, it thus seems that some farmers are aware of climate change and the impacts it can have.

Given that the forecasts of farmers about future climate are inherently unknown, I will use two approaches to approximate the weight ω. The first approach, and my main specification, is where I take an agnostic approach and let the weight vary from zero to one. An alternative approach is where I estimate the weight that best fits the data, with a non-linear least squares approach as proposed by SCD. Using equation 1.7 and plugging it into equation 1.4 gives the equation that can be empirically estimated:

$$P_t \approx \left(\frac{1+r}{r}\right) a + \mathbf{b}\left(\left(1-\omega_t\right)\mathbf{I}_t^{nc} + \omega_t \mathbf{I}_t^{mc}\right). \tag{1.8}$$

The weights in this equation can be interpreted in several ways. Farmers could weight different forecast models, which would imply that farmers take climate projections into account. However, there is no need for farmers to believe in climate change to predict increases in climate. Kala (2017) shows that farmers often place a higher weight from temperatures of recent years. Therefore, if farmers experience warmer temperatures, in recent years, they might linearly extrapolate towards the future or assume higher (or lower) climate levels than the thirty-year average. For an overview of learning models, see Kala (2017).

Besides differences across space, differences across time can also be utilized to estimate the impact of temperature on climate. If the price of land, given by equation 1.8, is differenced between periods for a county, the resulting impact on the value of land will be

$$P\left(I_{t_2}\right) - P\left(I_{t_1}\right) = b\Delta I_{t_2,t_1}. \tag{1.9}$$

1.2.2 Evaluating the Net Present Discounted Value Impact of Any Two Different Paths and Connection to the Literature

In this paper, I aim to evaluate the impacts of climate change on agriculture. Previously in the literature, the predominant approach has been to compare steady states across time. For example, Schlenker, Hanemann and Fisher (2005) use a uniform 5-degree Fahrenheit increase in temperature and a uniform 8-percent increase in precipitation to estimate climate damages. SHF compare damages based on differences in climate between the years 2020-2049 and 1960-1989. They use the U.K. Met Office Hadley Model, HadCM3, which was prepared for the fourth IPCC Assessment Report. SHF use four standard emissions scenarios B1, B2, A2, and A1F1 from the IPCC Special Report on Emission Scenarios (SRES) (Nakicenovic, 2000) emission scenarios. With the B2 and A scenarios, damages during the mid-century range are around -20 percent of farmland values compared to the climate in 1982.

While comparing damages gives a sense of the magnitude of climate change, there are some challenges with these exercises. First, the climate is not expected to stay constant in 2050. Moreover, farmers will almost surely be aware of the negative, or positive, impact of climate change on their crops and will more readily incorporate additional expected future changes. As a result, the conceptual exercise of a constant climate in 2050 is unlikely to happen. While cross-sectional estimates with NC forecasts can be rescaled, the second challenge is that different farmer forecasts are much more difficult to build into the traditional model that uses the level of climate at a time t.

In addition, as SCD point out, a present-discounted value approach is the more policy-relevant variable, as policymakers would be interested in the marginal impact of ton of carbon of CO2 on agriculture. The strength of the framework by SCD is that the coefficient allows for the comparison of any two paths $\mathbf{I}_{t_1,1}$ and $\mathbf{I}_{t_1,2}$, where the change in the value of land would be given by

$$\begin{aligned} P_t\left(\mathbf{I}_{t_1,2}\right) - P_t\left(\mathbf{I}_{t_1,1}\right) &= a + \mathbf{b}\mathbf{I}_{t_1,2} - a - \mathbf{b}\mathbf{I}_{t_1,1} \\ &= \mathbf{b}\left(\mathbf{I}_{t_1,2} - \mathbf{I}_{t_1,1}\right). \end{aligned} \tag{1.10}$$

While this change can be calculated for any path, I will provide estimates for a mean predicted climate change path, relative to a constant 2002 climate. SCD prefer to estimate the actual change in land values as the difference between the best fit of farmer's expectations and a constant climate. My damages can be multiplied by ω to obtain similar results..

1.2.3 The Importance of the Discount Rate for the Present Discounted Value Calculations

In order to calculate the impact of climate change, a choice has to be made on the discount rate. This choice has been widely debated in the literature (Nordhaus 2007). The Interagency Working Group on the Social Cost of Carbon (2010) settled on a discount rate of 3 percent, although they consider discount rates of 1 and 5 percent as well.[8] The motivation for these discount rates is that they consider the discount rate of households for consumption the relevant discount rate. Another view is put forward by Becker, Murphy and Topel (2011) who argue that the discount rate should be based on market rates of return and discuss the possible alternatives. They calculate present discounted damages for mortality with discount rates between 6 to 8 percent.

An empirical approach for agriculture is put forward by SHF. They create a proxy for the discount rate as the ratio of the net cash income to farmland values. They calculate this for the census years of 1987, 1992, and 1997. They find that the implicit discount rate of farmers is 4.65 percent.

In the light of these arguments, I will use a discount rate of 5 percent as my main specification, though I will present the results for the 3 and 8 percent as well.

1.2.4 Possible Bias from Incorrect Specifications

If an econometrician could observe the actual forecasts of farmers, then there would be no bias in the regression. However, as the expectations of farmers are unknown, some method of approximation is needed. To illustrate the possible bias from incorrect specifications, I convert equation 1.8 into an empirical counterpart

$$P_t = \alpha + \beta \left(\left(1 - \omega_t\right) \mathbf{I}_t^{nc} + \omega_t \mathbf{I}_t^{mc} \right) + e_i. \tag{1.11}$$

If however, the regression is estimated with $\omega = 0$ (the "No Change" forecast), or $\omega = 1$ (the "Mean Change" forecast), then the respective bias becomes

8. SCD give the following calculations to think about the impact of different discount rates on page 29, footnote 27: "For example, a constant revenue stream reaches 95% of its discounted value after 98 years with a discount rate of 3%, while this takes 297 years with a discount rate of 1% and 58 years with a discount rate of 5%."

$$
\begin{aligned}
\widetilde{b}_{I^{nc}} &\rightarrow b \cdot \left((1-\omega)\, \rho_{I^{nc} I^{mf}} \frac{\sigma_{I^{mf}}}{\sigma_{I^{nc}}} + \omega \right) \\
\widetilde{b}_{I^{mc}} &\rightarrow b \cdot \left((1-\omega) + \rho_{I^{nc} I^{mf}} \frac{\sigma_{I^{cc}}}{\sigma_{I^{nc}}} \omega \right),
\end{aligned}
\tag{1.12}
$$

where ρ denotes the correlation between the two present discounted variables. Given that $\sigma_{I^{mf}} > \sigma_{I^{nc}}$ empirically, and $\rho_{I^{nc} I^{mf}}$ is close to one for the temperature coefficients, the true coefficient would be bound between the two approaches. The traditional NC forecast would underestimate the coefficients, whereas a pure MC forecast would overestimate them. SCD find that the coefficients are indeed underestimated, but they fail to point out that the combined damages need not be higher. If the coefficients on beneficial coefficients, the growing degree days, rises relatively more than the killing degree days, then climate damages might be overstated. Therefore, the a-priori bias of damages is unclear.

In addition, a similar bias can be calculated for the long differences approach. However, since the expectations in 1978 are harder to approximate, I will make the additional assumption that the forecasts in 1978 were indeed constant but allow the forecasts in 2002 to vary. In addition, imagine that farmers were indeed to use the MC forecasts for 1978. A similar derivation for the bias of the traditional NC forecast would then yield

$$
\begin{aligned}
\widetilde{b}_{I^{nc}} \quad &\rightarrow \quad \frac{Cov\left(I^{nc}_{t_1} - I^{nc}_{t_0}, P\left(I^{mc}_{t_1}\right) - P\left(I^{mc}_{t_0}\right)\right)}{V\left(I^{nc}_{t_1} - I^{nc}_{t_0}\right)} \\
&= \quad b \left(\frac{\sigma_{I^{nc}_{t_1}, I^{mc}_{t_1}} + \sigma_{I^{nc}_{t_0}, I^{mc}_{t_0}} - \sigma_{I_0, I^{mc}_{t_1}} - \sigma_{I_1, I^{mc}_{t_0}}}{\sigma^2_{I^{nc}_{t_1}} + \sigma^2_{I^{nc}_{t_0}} - 2cov\left(I^{nc}_{t_1}, I^{nc}_{t_0}\right)} \right).
\end{aligned}
\tag{1.13}
$$

1.2.5 Profit-Maximizing Choices of Farmers

The previous sections dealt with the theoretical framework of the price of land as the discounted value of all future rent. In this section, I delve deeper into the profit-maximizing framework of farmers that is at the heart of the ricardian model. I will present a theoretical foundation, which is drawn from Mendelsohn, Nordhaus, and Shaw (1992), and present some approximations for the bias that can result from not holding prices constant.

First, suppose there is a demand system of n equations for several agricultural outputs:

$$\begin{aligned} P_1 &= D^{-1}\left(Q_1,\, Q_2,\, \ldots,\, Q_n,\, Y\right) \\ &\;\;. \qquad\qquad\quad . \\ &\;\;. \qquad\qquad\quad . \\ &\;\;. \qquad\qquad\quad . \\ P_n &= D^{-1}\left(Q_1,\, Q_2,\, \ldots,\, Q_n,\, Y\right). \end{aligned}$$

Where each output Q_i is a function of the environmental variables $\mathbf{E}$ and a vector of capital inputs $\mathbf{K}_i$ so that the production function and cost functions can be written as

$$Q_i = Q_i\left(\mathbf{K}_i,\, \mathbf{E}\right),\; i = 1, \ldots,\; n.$$

$$c_i = c_i\left(Q_i,\, \mathbf{R},\, \mathbf{E}\right),\; i = 1, \ldots,\; n.$$

Where $\mathbf{R}$ denotes the factor prices. Every firm, which is assumed to produce one good, will maximize its profits with respect to Q_i subject to a price P_i. Next, denote the price for land as p_{LE}. A profit-maximizing firm will thus maximize the following equation

$$max_{Q_i}\; P_iQ_i - c_i\left(Q_i,\, \mathbf{R},\, \mathbf{E}\right) - p_{LE}L_i.$$

With the associated first order conditions $P_i\frac{\delta Q_i(\mathbf{K}_i,\, E)}{\partial K_{ij}} - R_j = 0,\ \forall j$. Furthermore, I assume perfectly competitive markets that drive profits for a single use of land to zero due to entry and exit in the long run:

$$P_iQ_i - c_i\left(Q_i,\, \mathbf{R},\, \mathbf{E}\right) - P_{LE}L_i = 0,\; i = 1, \ldots,\; n. \tag{1.14}$$

The ricardian approach will now difference the two highest values of each land under two different climate specifications, E_A and E_B. If E_A has a harsher climate than E_B, then the maximum value of the land, holding other environmental factors constant, will lead to a loss of land value. These different climates have different outputs, Q_A and Q_B associated with them. Thus, farmers will lose (or gain) a value of

$$V\left(\mathbf{E_A} - \mathbf{E_B}\right) = \int_0^{Q_B} \sum D^{-1}\left(Q_i\right) dQ_i - \sum C_i\left(Q_i,\, R,\, E_B\right) -$$
$$\int_0^{Q_A} \sum D^{-1}\left(Q_i\right) dQ_i - \sum C_i\left(Q_i,\, \mathbf{R},\, \mathbf{E_A}\right).$$

However, if prices are assumed to be constant, this expression simplifies further to

$$V\left(\mathbf{E_A} - \mathbf{E_B}\right) = \mathbf{PQ_B} - \sum C_i\left(Q_i,\, \mathbf{R},\, \mathbf{E_B}\right) - \mathbf{PQ_A} - \sum C_i\left(Q_i,\, \mathbf{R},\, \mathbf{E_A}\right).$$

Using the zero-profit condition of equation (1.14), this expression can be further simplified to yield the change in surplus in terms of land values:

$$V\left(E_A - E_B\right) = \sum_i \left(P_{LEB} - P_{LEA}\right) L_i.$$

Where the prices for a land unit are evaluated at the old and the new unit. This expression is the foundation for the welfare statements in the empirical section, as it corresponds to the changes in land values which will be the dependent variable.

1.2.6 *Welfare Measurements with and without Price Changes*

The ricardian approach has been criticized because it does not account for price changes and therefore can underestimate damages and overestimate gains (Cline 1995). Furthermore, I present a model from Mendelsohn and Nordhaus (1999) to demonstrate that resulting biases are small. To analyze these biases, they present a simple demand and supply linear framework with a range of supply and demand elasticities. The demand curve is $Q_d = \alpha_0 - \alpha_1 P$, and the supply curve is represented by $Q_s = \beta_0 + \beta_1 P$. Denote a climate shock by β_0^*. For an adverse climate evolution, β_0^* will be lower than β_0. Denote the original market outcomes by Q_0 and P_0 and the new market outcomes as Q_1 and P_1. In the linear framework, the social surplus is $W(\beta_0) = \frac{1}{2}\left[\frac{\alpha_0}{\alpha_1} + \frac{\beta_0}{\beta_1}\frac{(\alpha_0\beta_1+\alpha_1\beta_0)}{(\alpha_1+\beta_1)}\right]$. The full change in welfare is given by the difference between $W\left(\beta_0^*\right)$ and $W(\beta_0)$. In the ricardian approximation, the estimation will yield the difference in producer surplus. However, this estimation will underestimate the damages by the triangle above the original price and can be written as

$$B = \frac{1}{2}(P_1 - P_0)(Q_0 - Q(\beta_0^*, \beta_1, P_1)) \tag{1.15}$$

and can be further simplified to

$$B = \frac{1}{2}(P_1 - P_0)(\beta_0 - \beta_0^*). \tag{1.16}$$

The fractional bias of the ricardian regression can then be written as $\frac{B}{\Delta W}$ and simplified to

$$\frac{B}{\Delta W} = \frac{\beta_1\left(\beta_0 - \beta_0^*\right)}{2\alpha_0\beta_1 + \alpha_1\beta_0 + \alpha_1\beta_0^*}. \tag{1.17}$$

Dividing by β_0 and multiplying and dividing by $\frac{P_0}{Q_0}$ yields

$$\frac{B}{\Delta W} = \frac{\epsilon_s\left(1 - \frac{\beta_0^*}{\beta_0}\right)}{2\frac{\alpha_0}{\beta_0}\epsilon_s + \left(1 + \frac{\beta_0^*}{\beta_0}\right) \mid \epsilon_d \mid}. \tag{1.18}$$

This expression allows to calculate the bias in terms of the elasticities of demand and supply, as well as the percentage supply shock $\frac{\beta_0^*}{\beta_0}$. I calculate these elasticities in table 1.1 using a range of reasonable agricultural elasticities.[9] With a 10 percent supply reduction, the bias ranges from 0.3 to 3.5 percent. On the other hand, a 25 percent supply shock, which is very large, still only has a bias between 0.7 and 9 percent. The biases thus seem very

9. Note that Mendelsohn et al. (1992)put the ratio of the intercepts equal to 1. This ratio seems a very conservative number, and for any more reasonable high number, the biases will be much lower than those in table 1.1.

Table 1.1: Percentage Bias from Constant Price Assumption

	Percentage Bias		
Supply Elasticity	DE = -0.5	DE = -1.0	DE = -2.0
10-Percent Reduction in Supply			
0.1	0.9	0.5	0.3
0.5	2.6	1.7	1.0
1.0	3.4	2.6	1.7
25-Percent Reduction in Supply			
0.1	2.3	1.3	0.7
0.5	6.7	4.5	6.7
1.0	8.7	2.8	4.5

Note: The equation ($B/\Delta W$) gives the expression to calculate the percentage bias. This bias is calculated with the associated supply and demand elasticities, as well as the supply shock.

small and indicate that the size of the shock matters much more than the potential bias.

1.3 Data Sources and Summary Statistics

1.3.1 Land Values, Soil, and Socio-Economic Variables

I use land value data from the National Agricultural Statistics Service (NASS).[10] I standardize the value of land and buildings to 2002 dollars. [11] Besides land values, I include the quality of the soil, as well as socio-economic variables. For the socio-economic variables, I follow previous research and use population density and per capita income (DG 2007). I use data from the Bureau of Economic Analysis, using the yearly per capita income measure for counties.[12] For soil variables, I use the soil dataset from MNS, who constructed this dataset

10. The years of 1982 to 2002 come from the Schlenker, Hanemann, and Fisher (2005) data appendix. The 1978 data census were obtained from Haines et al. (2016) and downloaded from ICPSR (https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/35206).

11. I construct a deflator using the DG data for comparison purposes. I construct this deflator using the ratio of nominal land values to their land values, which gives a unique deflator for each year. I then use this deflator for the other variables. Using the BEA GDP deflator, this conversion is almost exactly matched (the CPI deflator gives slightly worse results). I obtained theses deflators from https://fred.stlouisfed.org/series/A191RD3A086NBEA.

12. Obtained from https://www.bea.gov/regional/downloadzip.cfm. Note that Schlenker, Hanemann, and Fisher (2015) use data from the “County and City Data Book” to obtain this information. This dataset

from the National Resource Inventory (NRI) (http:// www.nrcs.usda.gov/technical/NRI/). The NRI surveys approximately 800,000 sites to obtain soil samples and land characteristics. This survey occurs during census years. County level data are then obtained by taking a weighted average across the nearest sites of the NRI survey. I will use the fraction of flood-prone acres in a county, the K-factor , the average slope length, the fraction of sand, the fraction of clay, and the fraction of irrigated land. In addition, these soil variables are supplemented with the permeability, moisture capacity, and salinity of the soil in a county.

I follow SHF and use all counties east of the 100th meridian in my data as my main sample.[13][14] Water impacts land values differently in the west compared with the east and has been discussed and summarized in Cline (1996). A key argument is that water has different marginal costs as many farms in the west have government-subsidized water. These state subsidies per acre often exceed land values in the east (SHF). Moreover, much of the water in western counties arises from groundwater and aquifers, which give rise to different adaptation strategies (Hornbeck and Keskin 2014).

1.3.2 Historic Climate Data

To measure climate, I use the "degree days" concept. Degree days, which represent heating units, have become a standard way to measure temperature in the agronomy literature (see Schlenker, Haneman and Schlenker 2006; DG). Degree days capture the cumulative exposure of crops to certain temperature ranges. Therefore, degree days can capture the exposure

has the variable for the years 1988, 1994, and 2000 and SHF use this to interpolate between years to obtain census year variables.

13. I use the longitude measure of Schlenker and Roberts (2009) where possible. For the additional counties in my data that are not in this dataset, I use the longitude measure from the following site: https://simplemaps.com/data/us-cities

14. Note that Schlenker, Hanemann, and Fisher (2005) prefer the specification of counties that are rural and dry-land when using the MNS climate variables. However, SHF demonstrate that this analysis does not hold for degree days. They define rural as counties where the population is less than 200.000 and the population density is less than 400 per square mile. They define dry-land as the counties that have irrigation for less than 20 percent. Ortiz-Bobea follows SHF in analyzing all variables and controlling through the per capita income and population density, while SCD focus on non-urban counties.

to extreme temperatures that are missed by average monthly temperatures. For example, Schlenker and Roberts (2009) analyze the impact of temperature on corn, soybeans, and cotton, using a panel data approach. Using degree days, they compare a flexible polynomial approach, a bin approach, and a piecewise-linear function. They document that the piecewise linear-function performs nearly as well as the fully flexible polynomial fit. In addition, they find that the impacts follow a linear form for corn, cotton and soybeans, with a threshold for each crop at 29, 20 and 32 °C. Burke and Emerick (2016) execute a similar analysis for corn and soybeans and find the optimal thresholds to be around 29 and 30 °C. To calculate the growing and killing degree days, one can either use the estimated thresholds by Schlenker and Roberts or estimate them using a loop that searches for the best fit on the yield data. This calculation can then be repeated for each crop, and for each selected time-horizon. SHF show that these degree days also provide an excellent fit for land values.

In my paper, I use the degree day data from Schlenker and Roberts.[15] Furthermore, Burke and Emerick (2016) have calculated climate projections for these degree days. In my current write-up, I will use degree day ranges from 0 °C to 29 °C and call these growing degree days (GDD), as well as those above 29 °C and call these killing degree days (KDD). Although the Schlenker and Roberts data includes temperature bins of 1 °C, the climate projections by BE only are from the 0 to 29 °C range and above. Thus, this precludes an analysis using the square root of 34 °C as in SHF.[16][17] The precipitation measure is calculated as the total rainfall from April 1st to September 31st. I compute climate variables as their thirty-year average.

15. I used the data provided in the data provided by the Burke and Emerick paper, which can be downloaded online.

16. I did obtain RCP data for a couple of climate models. However, they were not yet bias-corrected and only started in 2010, so I opt here to not use them.

17. The Energy Policy Institute of Chicago does continue to work on these projections and will have them ready at some future time.

1.3.3 Climate Change Predictions and Climate Model Uncertainty

For climate change predictions, I utilize the data by Burke and Emerick (2016) who have generated climate predictions by 2050 for the A1B-scenario, which is a "business-as-usual" scenario. BE have bias-corrected these projections (Aufhammer et al. 2013). They calculated the predicted climate by 2050, calculated as the average of 2040-2060. They then subtracted the climate of historical projections in 2000 to obtain predicted changes for each county. I refer to their paper for more details on the generation and features of these climate models.

1.3.4 Summary Statistics

Agricultural, Soil, and Climate Statistics

Merging the above datasets, I obtain a balanced sample of 2,340 counties.[18] Table 1.2 summarizes the climate and socio-economic variables for the different census years, weighted by the acres of farmland. The average amount of growing degree days in the sample is around 3,660, while the average killing degree days is around 70. These averages stay fairly constant over time, though this average change over time masks a lot of individual variation within counties over time, which the next paragraph discusses. The average value of land in the sample is $1,655 per acre and the total value is $830 billion. Figure 1.2 displays the distribution of the growing and killing degree days spatially.

Table 1.3 summarizes all of the variables for 2002. I have included both the level of the growing and killing degree days. In addition, I have included the difference between the predicted mean climate change and a 2002 constant climate. These differences will be used to multiply the coefficients from the regressions to obtain the impacts of climate change.

For the long differences approach, the question remains exactly how much variation there

18. Not all counties east of the 100th meridian are included. as the merge with the soil data of MNS and the climate data decreases the number of observations. Besides missing soil or climate data, the majority of these missing counties are 51 counties in Virginia who are cities.

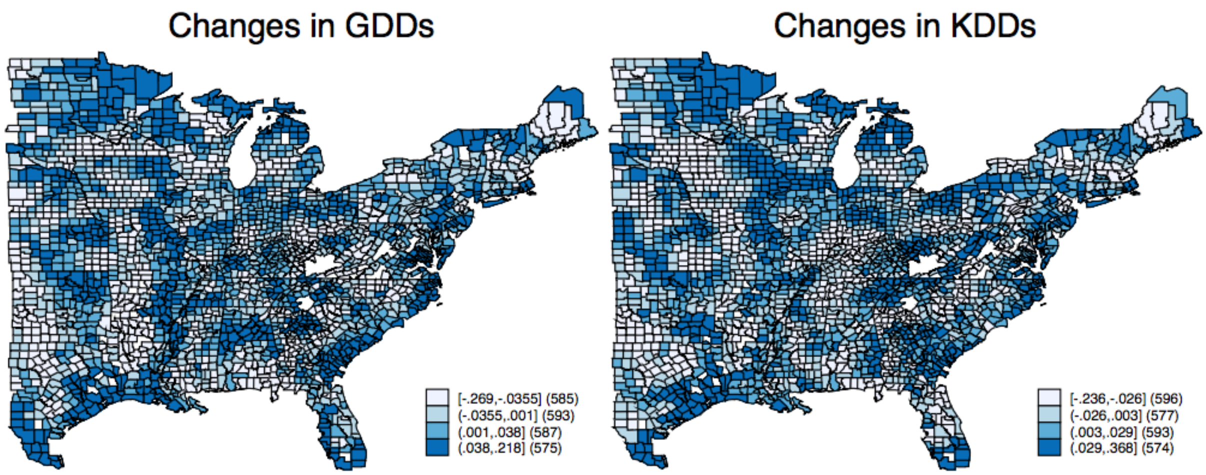

Figure 1.1: Spatial Variation in Climate Variables between 1978 and 2002

Note: This graph shows the climate changes in growing and killing degree days from 1978 to 2002, after subtracting the average state change. These demeaned changes are then divided by the predicted changes according to the mean predictions across climate model scenarios.

is relative to the changes in climate. Burke and Emerick (2016) show that there is a surprising amount of climate variation within counties over time. They use this climate variation to compare short-run and long–run responses of yields to climate changes for corn and soybeans. I utilize their insight and apply it to land values. Figure 1.3 displays this climate variation. To construct this figure, I create the differences in climate from 1978 to 2002 for each county, where I have subtracted the mean change for the state. Then I divide this change by the mean predicted climate change across climate models by 2050. The histogram reveals that the range of climate variation varies relative to predicted climate change from approximately -25 percent up to 25 percent. Even though climate, by definition, changes slowly, there is useful information that can be utilized over time. In addition, the twenty-four years between 1978 and 2002 also give farmers time to adjust their practices, thus mitigating the adjustment cost concern (Kelly et al. 2005).

Table 1.2: Weighted Summary Statistics for Different Census Years

	1978	1982	1987	1992	1997	2002
Av. value of land	1988.8	1759.5	1198.9	1182.0	1381.1	1655.0
Growing degree days	3666.6	3676.1	3657.9	3675.8	3663.8	3669.3
Killing degree days	83.7	85.0	78.9	81.3	78.3	80.3
Precipitation (in cm)	55.3	55.3	56.3	55.2	56.4	56.2
Per capita income	15699.1	16301.5	18328.7	20169.1	22444.8	24706.6
Population density (sq. mile)	73.2	75.5	75.6	77.0	81.5	84.1
Observations	2340	2340	2340	2340	2340	2340

Averages are calculated for a balanced panel of 2,340 counties. All entries are weighted by the acres of farmland. All dollar values are in 2002 constant dollars.

Table 1.3: Summary Statistics for 2002

	Mean	σ	Min	Max
Land in farms (th. acres)	214.53	(179.08)	1.10	2042.70
Av. value of land	2227.27	(1977.51)	241.00	26419.00
Growing degree days	3662.80	(528.27)	2331.60	4840.90
Killing degree days	66.37	(57.02)	0.14	404.60
Precipitation (in cm)	59.82	(9.33)	33.59	97.74
Difference in PDV GDDs	2851.87	(457.89)	1384.85	3650.93
Difference in PDV KDDs	701.28	(371.45)	35.84	2125.17
Difference in PDV Precipitation	-4.75	(20.75)	-80.29	45.60
Fraction sand	0.01	(0.29)	-0.08	0.92
Salinity	-0.01	(0.04)	-0.02	0.75
Fraction flood-prone	-0.00	(0.21)	-0.18	0.82
Wetlands	0.01	(0.11)	-0.06	0.83
K-Factor	0.00	(0.07)	-0.19	0.19
Slope length	-0.20	(1.03)	-1.93	8.92
Moisture Capacity	-14.38	(262.87)	-259.20	1707.24
Permeability	-214.16	(3517.57)	-3052.84	65714.95
Per capita income (thousand $)	24.94	(5.50)	12.75	64.81
Population density (sq. mile)	143.56	(311.21)	0.80	5634.90

Averages are calculated for 2,340 counties. All entries are simple averages weighted by the acres of farmland. All dollar values are in 2002 constant dollars.

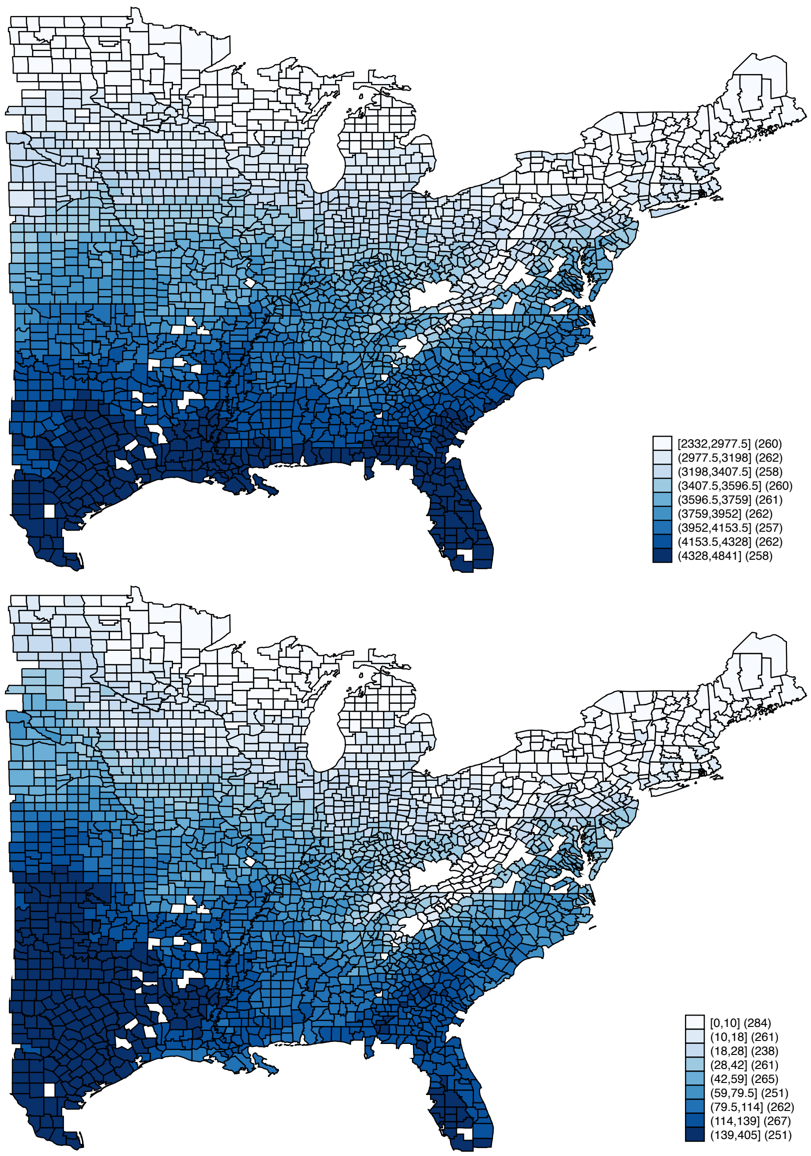

Figure 1.2: Growing and Killing Degree Day Climate in 2002

Note: This figure displays the number of growing and killing degree days in each county in 2002, measured as the thirty-year average from 1971-2001.

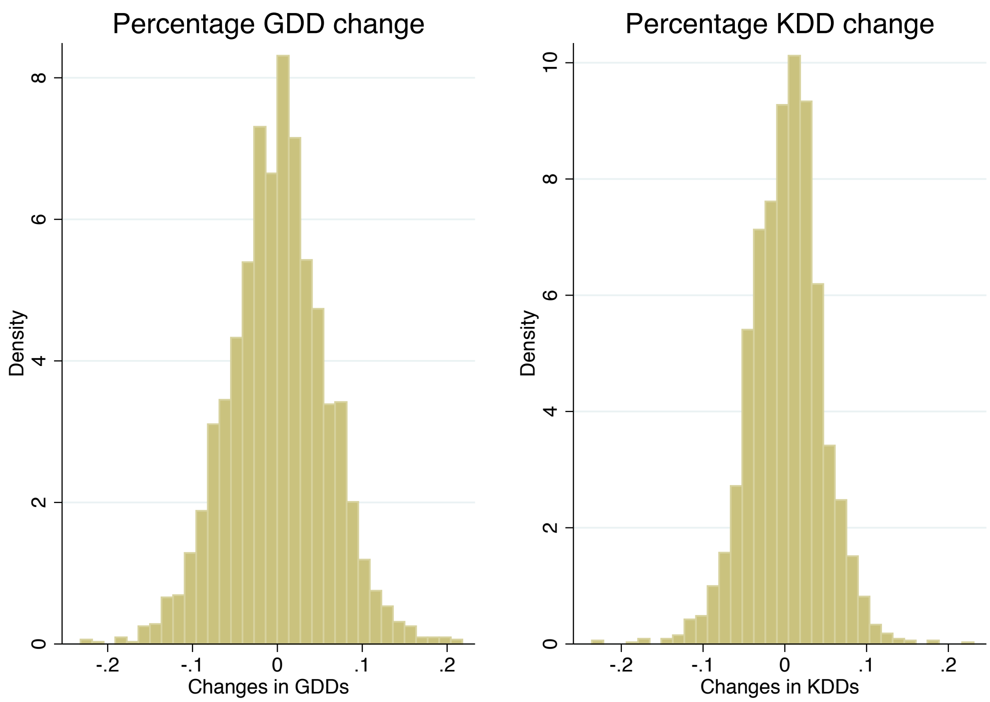

Figure 1.3: Variation in Climate between 1978 and 2002
Note: This graph shows the climate changes in growing and killing degree days from 1978 to 2002, after subtracting the average state change. These demeaned changes are then divided by the predicted changes according to the mean predictions across climate model scenarios.

Climate Change Statistics

For predicted climate changes, Figure 1.4 documents the spatial component of changes by 2050 for the mean predicted climate change. Given that I linearly interpolate the predicted climate change, this figure is similar to the present discounted degree day figures. Figure 1.4 shows that northern counties are set to gain many more growing degree days relative to the south, as well as much fewer killing degree days. These changes arise because a change from say 24 to 25 °C yields an additional growing degree day, whereas a change from 32 to 33 °C yields an additional killing degree day.

Figure 1.5 demonstrates the average changes in the climate variables across the different climate models. Figure 1.5 is a dot plot, where each dot represents a climate model an are stacked horizontally for comparable ranges. For growing degree days, the range of the increase goes from a low of 194 up until 529. For killing degree days, the range varies from 50 to 200. While there are some attempts to attach different weights to these climate models (see Knutti 2010; Knutti et al. 2017), I will take the "democratic" approach to climate model uncertainty, where each model gets one vote. Burke et al. (2015) contrast the preference of climate scientists for an ensemble of climate models with the use of climate models in social science. They show that the median use of climate models across 200 publications in the social sciences is only two. Furthermore, they show that using one or two climate models can severely underestimate the range of damages.

1.3.5 Construction of Farmers' Forecasts about Future Climate

Beside a "no change" forecast, farmers can also forecast increases in temperatures. In order to construct these forecasts, I would ideally have year-by-year projections from the IPCC. Unfortunately, Burke and Emerick have only projected climate change for each county by 2050. Therefore, I approximate farmer forecasts of increased temperatures through a linear interpolation between 2002 climate and 2050 climate on a county-by-county basis. To asses this approximation, I use newer climate forecasts from the newest IPCC, which are built

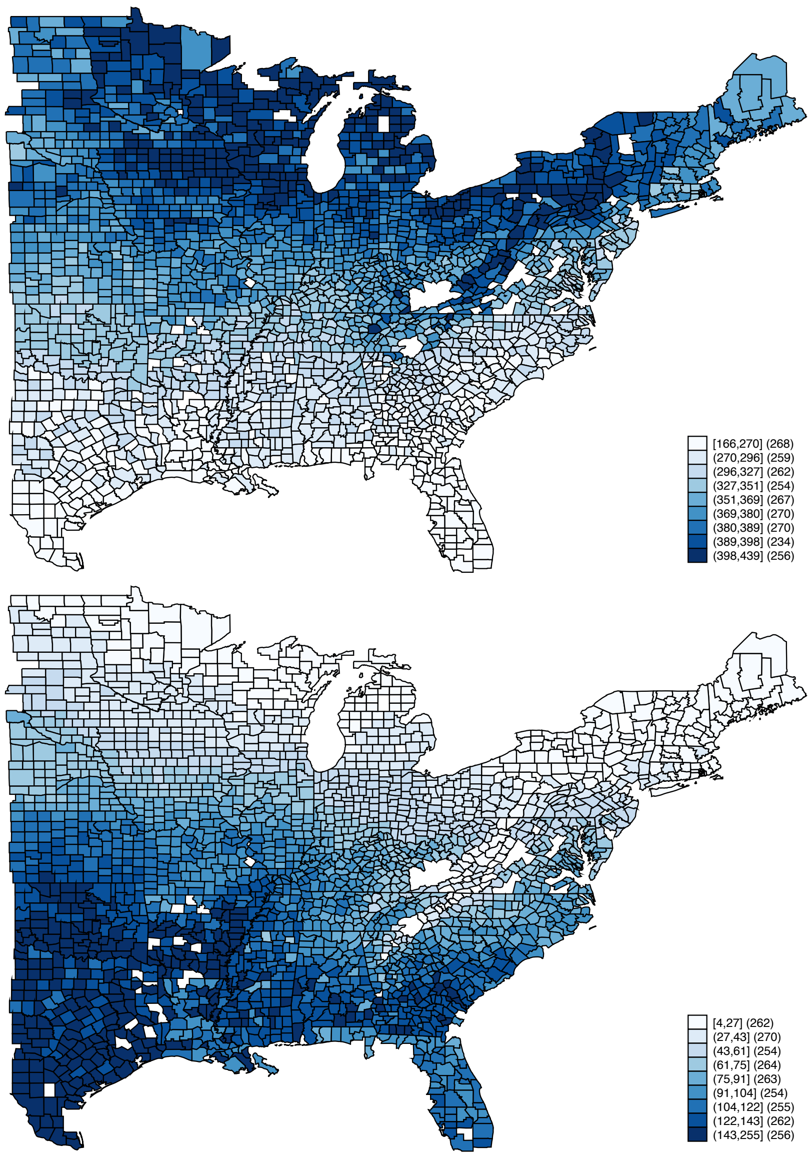

Figure 1.4: Predicted Mean Change in Growing and Killing Degree Days by 2050

Note: This figure displays the change in the number of growing and killing degree days in each county from 2000 to 2050, where the 2002 variable is calculated measured as the thirty-year average from 1971-2001.

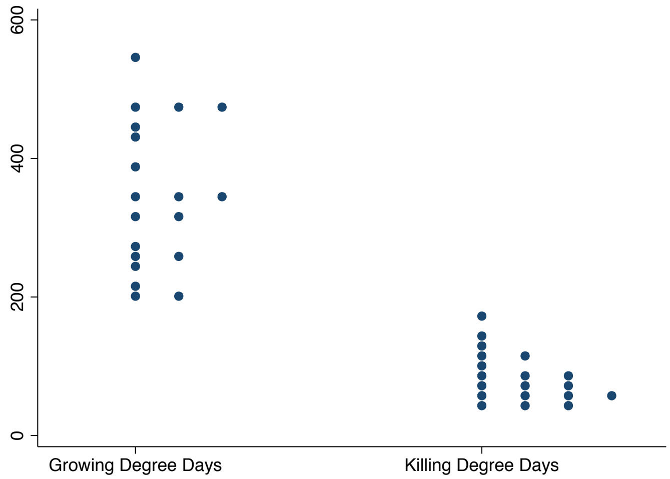

Figure 1.5: Predicted Climate Changes by 2050 for Temperature Variables across Different Climate Models
Note: This figure is a dot plot for the average change in the number of growing degree days and killing degree days in each county from 2000 to 2050 for the variety of climate models.

around Representative Concentration Pathways (RCPs).[19] While I have RCP year-by-year projections from 2010 to 2099, I chose not to use these for several reasons. The first reason is that these projections are not bias-corrected (Aufhammer et al. 2013). Second, the time series I have begins in 2010. Third, these RCPs and their projections were recently created, and thus would not have been in the information set of farmers in 2002.[20] In contrast, the IPCC forecasts from Burke and Emerick (2016) are much more likely to have been in the information set of farmers in 2002 than the newest forecasts. For these reasons, I do not utilize this RCP data. However, they do provide a benchmark to investigate the evolution of year-to-year growing degree day predictions relative to the linear interpolation method. Figure 1.6 graphically displays this interpolation and the RCP data. This linear interpolation approximates the trend and shape of the year-by-year RCP projections quite well.

19. I thank Gregory Dobbels in particular for creating and providing this data.

20. Of course, many of the climate models that are used are built upon their predecessors.

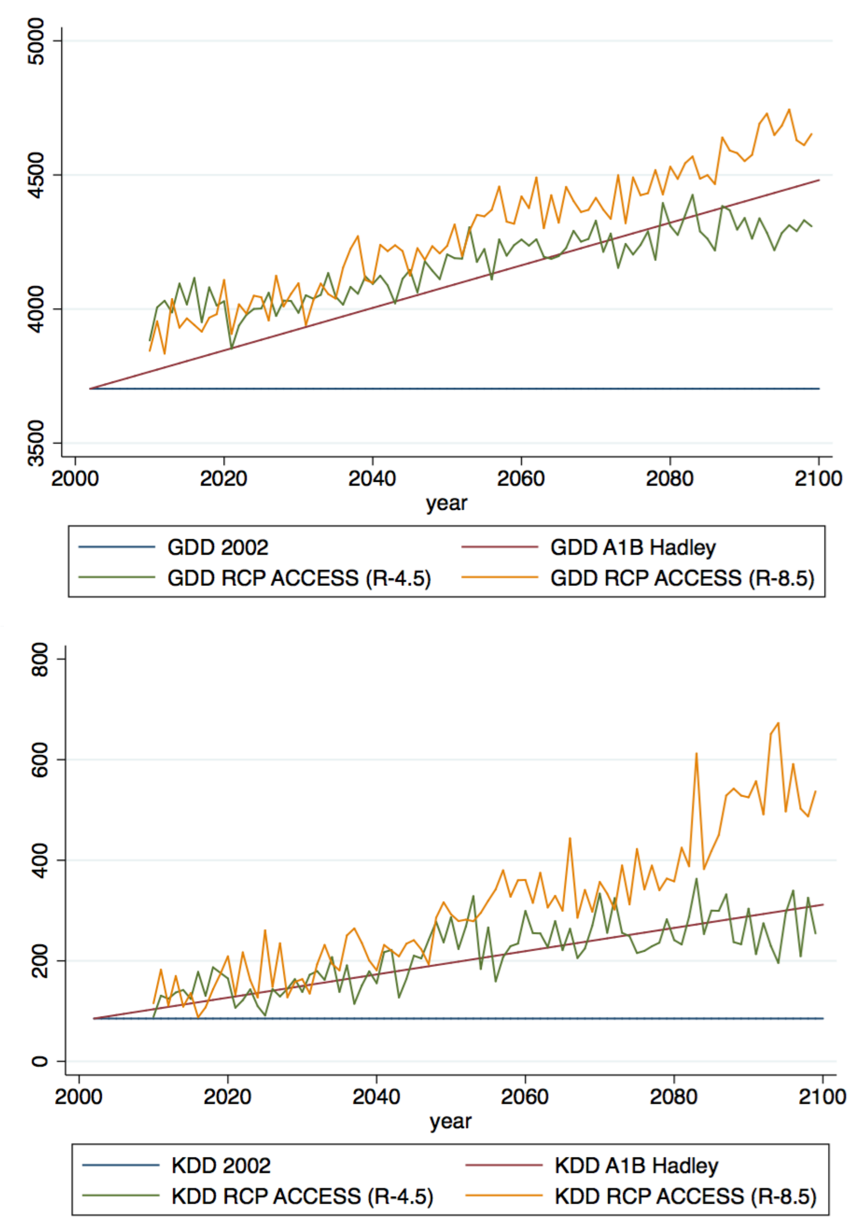

Figure 1.6: Comparison of Constructed Farmers' Forecasts

Note: These figures show the constructed growing and killing degree days for the sample. The blue line represents the growing days in 2002 and holds them fixed for the "No Change" forecast of farmers. The red line represents the linear interpolation for farmers forecasts using the A1B model forecast in 2050 and the climate in 2002 up until the end of the century. The yellow line represents the predicted growing degree days by year from the ACCESS model for the RCP 4.5 and 8.5 scenarios.

1.4 Econometric Strategy

1.4.1 Econometric Framework

I now present the empirical framework to estimate the relationship between climate and land values. To estimate equation 1.8, denote a county i in a state s in period t, the climate variables by $\mathbf{C}_{ist}$ and the soil and socio-economic variables by $\mathbf{X}_{ist}$. The value of land can then be specified as

$$P_{ist} = \alpha + \alpha_{ist} + \beta\left((1-\omega)\,\mathbf{I}_{ist}^{nc} + \omega\mathbf{I}_{ist}^{mf}\right) + \gamma\mathbf{X}_{ist} + u_{ist} \tag{1.19}$$

When the farmer utilizes a "No Change " forecast, which is predominant in the literature, the weight becomes zero which yields

$$P_{ist} = \alpha + \alpha_{ist} + \beta\mathbf{I}_{ist}^{nc} + \gamma\mathbf{X}_{ist} + u_{ist}. \tag{1.20}$$

Given that this index $\mathbf{I}_{ist}^{nc}$ can be rewritten as $\mathbf{I}_{ist}^{nc} \equiv \sum_{\tau=t}^{\infty} \mathbf{C}_{i,t}\left(\frac{1}{1+r}\right)^{\tau-t} = \left(\frac{1+r}{r}\right)\mathbf{C}_{ist}$, the estimation equation reverts to the standard hedonic equation:

$$P_{ist} = \alpha + \alpha_{ist} + \left(\frac{1+r}{r}\right)\beta\mathbf{C}_{ist} + \gamma\mathbf{X}_{ist} + u_i. \tag{1.21}$$

If farmers were to have forecasts that were identical to the IPCC models, than the weight ω would be equal to one and the regression becomes

$$P_{ist} = \alpha + \alpha_{ist} + \beta\mathbf{I}_{ist}^{mf} + \gamma\mathbf{X}_{ist} + u_{ist}. \tag{1.22}$$

While the theoretical framework was presented with the price of land, a broad range of papers in the agricultural literature use a log-linear specification. SHF, for example, test which specification best fits the data and find strong evidence in favor of using the natural logarithm of land values. I implement a box-cox test but cannot reject the linear or logarithm model. Therefore, I will present both sets of results. I further elaborate on how I calculate damages under each specification in the results section.

For weighting, DG discuss several weighting schemes and recommend weighting by the square root of acres of farmland. I also apply the modified Breusch-Pagan test, as recommended by Solon et al. (2013), and find that this test recommends weighting.

1.4.2 Review of Approaches and Identification Assumptions

Cross-sectional Regression

Before 1994, researchers investigated the impacts of climate change mostly through the use of input-output models for specific crops (for an overview, see MNS; Carleton and Hsiang 2016). In addition, there were general equilibrium models that investigated the response of several crops (Rosenzweig and Perry 1994). Yet in their seminal paper, MNS argued that these estimations will overestimate true damages. MNS argue that these models often have a very limited scope for substitution, as farmers can decide on a variety of substitution possibilities. For example, farmers can introduce new crops, switch among existing crops, introduce new technologies or use land for other purposes.

MNS take a revealed preference approach and argue that the rent of land is always equal to its highest use.[21] As a result, controlling for soil quality and a lot of other variables, they calculate the effect of temperatures and precipitation on farm values in 1982. The results are identified from counties with similar soil qualities and crops, but who have different climate variables.

However, this approach has been challenged as the cross-sectional variation might suffer from omitted variable bias (DG). DG find that the results of the cross-sectional analysis can vary with the census year and econometric specification. In light of this sensitivity, DG argue that there might be an omitted variable bias problem, though the bias and the magnitude

21. They assume the economy and land values are in a steady state equilibrium and that prices are fixed

are unknown.

In this approach, the inclusion of state fixed effects has been a point of contention. MNS do not include state fixed effects as they want to trace out the entire envelope across the different temperature regions. However, SHF argue for the inclusion of state fixed effects. They argue that state subsidies might be correlated with specific crops and potentially bias the estimates. They analyze the robustness of their pooled results and find that the exclusion of state fixed effects does not substantially alter their results from excluding state fixed effects. I obtain a similar finding in my regression results. For completeness and to follow the literature, I present the results both without and with state fixed effects in the robustness section.

Panel Data Approach

A second approach, which seeks to overcome these drawbacks, is the panel literature. The panel literature approach uses random weather variation across years to estimate the impacts on yields or profits, relative to their trend (DG; Schlenker and Roberts 2009; Dell, Jones, and Olken (2012); Moore and Lobell 2014; Deschênes and Greenstone 2011). The strength of this approach is that it overcomes the omitted variable bias. Using panel data allows to use of county fixed effects to control for unobserved heterogeneity on the county level using year-by-year variation (Schlenker and Roberts 2009; DG). However, this approach suffers from the drawback that year-to-year weather variation can be a poor proxy for more permanent climate changes. In addition, this approach limits adaptation possibilities from farmers. Weather fluctuations do not allow farmers the full range of adaptations that are possible in the long run. In the long run, farmers can adapt more, mitigating more of the damage through different technologies, seeds, or crop choice. Theoretically, the long-run adaptation can be lower than in the short run. For example, depletable aquifers can lead to more mitigation in the short run than in the long run. (Hornbeck 2012 ; Fisher et al. 2012). In addition, farmers can also adapt along the margins of taking up more crop insurance (Annan and Schlenker 2015). A third limitation is that this panel approach has been predominantly used to analyze crops. As such, this approach suffers from the limited adaptation possibilities that MNS were trying to address.

Long-Differences Approach

In this paper, I use a novel method that was recently developed by Burke and Emerick (2016) and goes back to Lobell and Asner (2003) . They propose using actual changes in climate within a county over time. For example, they analyze the responses of corn and soybeans to changes in climate from 1980 to 2000. However, they still only look at corn and soybeans, which restricts the range of adaptation that farmers can engage in.[22]

I leverage this idea to overcome the potential omitted variable bias problem with land values. In addition, I can still retain the advantage of using actual climate changes, not temporary weather fluctuations.[23] However, there is no free lunch. The variation using climate changes over time is less than in the cross-section. Yet I show in the data section that there is a surprising amount of climate variation within counties over time from 1978 to 2002.

Econometrically, the specification can be obtained by first differencing the cross-sectional equation for two different time periods,

$$P_{2002}\left(I_{2002}\right) - P_{1978}\left(I_{1978}\right) = \alpha_{is} + \beta\Delta\mathbf{I}_{ist} + \gamma\Delta\mathbf{X}_{ist} + \epsilon_{ist}.$$

In this equation, α_{is} denotes the state-by-year fixed effects. I include state-by-year fixed effects to account for the change in the average land value in that state over time. By using state fixed effects, I can allow for composition and price changes with the level effects by state. However, as SHFR (2012) point out, there might still be differences within the state

22. Burke and Emerick find little evidence for adaptation as the losses over a "short" panel (4 years) and a long panel are very similar.

23. Or put differently, I can utilize the strength of land values while eliminating the potential omitted variable bias problem from the cross-section.

due to price, though the county fixed effects in the long differences would account for that.

Within the long differences approach, I set the weight for 1978 equal to zero, so that farmers in 1978 believe that future climate will be equal to the climate in 1978. Another approach would be to take the historical data projections from the IPCC models going back to 1948. For 2002, I can let the weight on forecasts vary again and create NC and MC forecasts.

1.5 Results and Interpretation

1.5.1 Results for Main Specifications

Regression Results

Given this set-up, a reasonable question is to wonder whether a weighted forecast model improves upon an NC forecast model. Or said differently, whether there is additional information in the MC forecast that is not captured in the NC forecast. As a first test, I put both indices in the regression for the climate variables. These indices are statistically significant which indicates support for a weighted combination of the forecast. In subsection 1.5.3, I estimate the preferred weight for the cross-section with a non-linear least squares approach and find that estimated weights that are statistically significant.

For the forecast specifications, I report the traditional estimation with "No-change", as well as the "Mean Change" forecasts. These expectations should provide a reasonable bound for the true forecasts of farmers as discussed in the theoretical section. Table 1.4 presents the full estimation results for all the variables besides temperature. The signs on the "per capita income" and "population density" variables are as expected. Each of these variables has a positive impact on the value of land, which decreases with the level of these variables. Salinity, the fraction of sand, and the fraction of flood proneness each negatively impact the value of land. Similarly, increases in wetland and soil erosion decrease the price of land. However, slope length and moisture capacity positively influence the price of land.

Precipitation has an inverted U-shape influence on land values, as in SHF and Mendelsohn et al. (1996). The coefficients of precipitation are similar for the different cross-section specifications, but are much more noisily estimated with the long differences approach. The coefficients are not statistically significant at the 5-percent level and have decreased in magnitude, with their signs switching, which might indicate that the measurement error for precipitation is a potentially larger concern. However, given that the average precipitation change is close to zero, I find that the results for precipitation do not influence the total impacts that much, as can be seen in Figure 1.7. I find that similar patterns hold for the regression with the level of land values as the dependent variable in table 1.5. The exception is the coefficient of salinity, which switches sign but is not statistically significant at the 10-percent level. Furthermore, the long differences approach differences out the constant soil variables so they are not included. As mentioned in the data section, DG obtained the NRI over time, but find that the soil variables are nearly identical for all time periods.[24]

24. DG report the mean of their soil coefficients in Table 1. This table shows that slope length decreases in their specification form 218.9 in 2002 to 218.3 in 2002. Permeability changes from 2.90 to 2.88 in 2002. The other variables remain constant.

Table 1.4: Coefficient Estimates for the Models with the Logarithm of Farmland Value per Acre

	(1) NC:Pooled	(2) NC:2002	(3) MC:2002	(4) NC:LD	(5) MC:LD
Precipitation	0.0041***	0.0048***	0.0039***	-0.0031	-0.0012*
	(0.00089)	(0.00088)	(0.00063)	(0.0022)	(0.00059)
Precipitation squared	-0.0030***	-0.000035***	-0.000028***	0.000023	0.0000066
	(0.0000078)	(0.0000076)	(0.0000054)	(0.000018)	(0.0000058)
Fraction sand	-0.12**	-0.18**	-0.17**		
	(0.054)	(0.076)	(0.069)		
Salinity	-0.0062	-0.027	-0.20		
	(0.22)	(0.31)	(0.30)		
Fraction flood-prone	-0.064	-0.096	-0.096		
	(0.056)	(0.081)	(0.077)		
Wetlands	-0.35**	-0.49***	-0.51***		
	(0.16)	(0.15)	(0.14)		
K-Factor	-1.04***	-1.26***	-1.18***		
	(0.34)	(0.41)	(0.39)		
Slope length	0.041**	0.039*	0.038*		
	(0.016)	(0.020)	(0.019)		
Moisture Capacity	0.00035***	0.00021***	0.00020***		
	(0.000056)	(0.000065)	(0.000063)		
Permeability	-0.0000079***	-0.000015***	-0.000015***		
	(0.0000026)	(0.0000029)	(0.0000029)		
Per capita income	0.000055**	0.000036*	0.000034	0.000060***	0.000061***
	(0.000025)	(0.000020)	(0.000021)	(0.000012)	(0.000011)
Per capita income sq.	-4.3e-10	-2.1e-10	-2.0e-10	-7.9e-10***	-8.2e-10***
	(4.2e-10)	(3.0e-10)	(3.1e-10)	(2.1e-10)	(1.8e-10)
Population density	0.00095***	0.0011***	0.0011***	0.0015***	0.0016***
	(0.00012)	(0.00016)	(0.00016)	(0.00051)	(0.00046)
Population density sq.	-0.000019***	-0.000026**	-0.000025**	-0.000042***	-0.000044***
	(0.000000069)	(0.00000011)	(0.00000010)	(0.00000013)	(0.00000012)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.811	0.818	0.820	0.922	0.925
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the natural logarithm of the value of land per acre. See table 1.6 for regression specifications and the temperature coefficients. The only difference is that the coefficients are not multiplied by 100, except the coefficient on precipitation squared.

Table 1.5: Coefficient Estimates for the Models with Farmland Value per Acre

	(1) NC:Pooled	(2) NC:2002	(3) MC:2002	(4) NC:LD	(5) MC:LD
Precipitation	2.90**	2.96**	2.32*	-5.48	-3.45*
	(1.19)	(1.40)	(1.16)	(3.86)	(1.70)
Precipitation squared	-0.020**	-0.021*	-0.016*	0.045	0.028*
	(0.0097)	(0.011)	(0.0092)	(0.032)	(0.015)
Fraction sand	-220.0**	-271.9	-262.6		
	(95.5)	(200.3)	(198.1)		
Salinity	83.4	185.8	98.2		
	(338.9)	(368.9)	(351.9)		
Fraction flood-prone	-222.5**	-352.5**	-356.8***		
	(98.5)	(134.3)	(130.2)		
Wetlands	-533.2*	-842.5***	-856.7***		
	(288.0)	(295.2)	(285.0)		
K-Factor	-1843.9**	-1750.2**	-1727.6**		
	(831.4)	(704.9)	(691.7)		
Slope length	40.7**	31.8*	31.6*		
	(17.0)	(18.3)	(17.7)		
Moisture Capacity	0.43***	0.17	0.17		
	(0.14)	(0.13)	(0.13)		
Permeability	-0.0093	-0.023***	-0.023***		
	(0.0065)	(0.0050)	(0.0052)		
Per capita income	0.034	-0.070	-0.073	0.089**	0.090**
	(0.035)	(0.050)	(0.051)	(0.038)	(0.038)
Per capita income sq.	0.00000069	0.0000023**	0.0000023**	-0.0000010	-0.0000010
	(0.00000075)	(0.00000099)	(0.0000010)	(0.00000074)	(0.00000072)
Population density	2.06***	2.59***	2.58***	3.73**	3.75**
	(0.23)	(0.37)	(0.36)	(1.53)	(1.46)
Population density sq.	-0.00030***	-0.00047***	-0.00047***	-0.0010**	-0.0010***
	(0.000084)	(0.00013)	(0.00013)	(0.00038)	(0.00036)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.767	0.752	0.753	0.868	0.869
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the value of land per acre. See table 1.7 for regression specifications and the temperature coefficients.

Given these results, I will now focus on the coefficients of temperature as these are the key variables for estimating climate damages, as can be seen in Figure 1.7. Tables 1.6 and 1.7 show the results specifically for the temperature variables. Tables 1.8 and 1.9 show these regression coefficients but rescaled by the average predicted climate change in present discounted values. These tables thus give the total impacts of growing and killing degree days upon land values denoted in percentages of total land value.

Table 1.6 reports the coefficients of the regression that uses the logarithm of land values as the dependent variable. The coefficients on growing and killing degree days are positive and negative as expected. The growing degree days coefficient is the impact of a unit change in the present discounted value of growing degree days on the logarithm of land value. For the cross-sectional regression of 2002 with "No Change" expectations, the coefficient on growing degree days is 0.000019, which I multiplied by 100 to get the direct impact in percentage. A one unit increase in growing degree days thus has a 0.0019 percent impact on the current value of land. I can then multiply this coefficient by the difference in the growing degree days between the mean climate change forecast and a constant climate. This difference is 2,850 growing degree days for 2002. Thus, the total impact of growing degree days on land values of climate change is 5.53 percent, as reported in Table 1.8. This table rescaled the degree days by their respective differences in 2002. The exact impact of degree days is given by the conversion of $100 * (\Delta I \beta - 1)$, but is very close for most specifications. In addition, the impacts are slightly off with the averages rather than calculating them for each county and then averaging them. A similar interpretation holds for the killing degree days coefficient. The killing degree days coefficient of -0.014 implies a -0.014 percent on the price of land values. Scaled by a difference of 764, this yields an impact of -10.4 percent on land values. Note that these estimates are almost exactly the same as calculating the damages by county and then adding up the damages. All the coefficients are statistically significant at the 5-percent level except for the long differences coefficient with an NC forecast.

Tables 1.7 reports the coefficients when the level of land values is used as the dependent

Table 1.6: Regression Results Explaining the Logarithm of Farmland Value per Acre

	(1) NC:Pooled	(2) NC:2002	(3) MC:2002	(4) NC:LD	(5) MC:LD
Growing degree days	0.0025***	0.0019**	0.0029***	0.00090	0.0052**
	(0.00073)	(0.00073)	(0.00078)	(0.0031)	(0.0022)
Killing degree days	-0.014***	-0.014**	-0.015***	-0.018**	-0.028***
	(0.0037)	(0.0056)	(0.0047)	(0.0085)	(0.0057)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.811	0.818	0.819	0.922	0.925
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the natural logarithm of the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The coefficients are multiplied by hundred to show the change in percentage in land value from a unit change in the independent variable. The standard errors are clustered at the state level. The pooled regression is all census years from 1978 to 2002. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No-Change" forecast model is denoted by "NC" and the "Mean-Change" forecast model as "MC".

Table 1.7: Regression Results Explaining Farmland Value per Acre

	(1) NC:Pooled	(2) NC:2002	(3) MC:2002	(4) NC:LD	(5) MC:LD
Growing degree days	0.024	0.015	0.025	0.042	0.053
	(0.015)	(0.019)	(0.020)	(0.068)	(0.065)
Killing degree days	-0.14*	-0.19	-0.20*	-0.69***	-0.46***
	(0.084)	(0.12)	(0.10)	(0.22)	(0.17)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.767	0.752	0.753	0.868	0.868
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The standard errors are clustered at the state level. The pooled regression is all census years from 1978 to 2002. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No-Change" forecast model is denoted by "NC" and the "Mean-Change" forecast model as "MC".

Table 1.8: Rescaled Regression Results Explaining the Logarithm of Farmland Value per Acre

	(1) NC:Pooled	(2) NC:2002	(3) MC:2002	(4) NC:LD	(5) MC:LD
Growing degree days	7.09	5.53	8.34	2.60	14.8
	(2.11)	(2.11)	(2.25)	(8.77)	(6.40)
Killing degree days	-10.3	-10.4	-11.8	-13.7	-21.8
	(2.84)	(4.30)	(3.61)	(6.46)	(4.39)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.811	0.818	0.819	0.922	0.925
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the natural logarithm of the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The coefficients are multiplied by hundred to show the change in percentage in land value from a unit change in the independent variable. The standard errors are clustered at the state level. The temperature variables are rescaled by the average weighted change between the present discounted value of predicted climate change and a 2002 contant climate. The coefficients thus give the impact as a percentage of total land value in the sample in 2002, which is $830 billion. The pooled regression is all census years from 1978 to 2002 contant climate. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "NC" and the "Mean Change" forecast model as "MC".

Table 1.9: Rescaled Regression Results Explaining Farmland Value per Acre

	(1)	(2)	(3)	(4)	(5)
	NC:Pooled	NC:2002	MF:2002	NC:LD	MF:LD
Growing degree days	4.18	2.61	4.41	7.24	9.24
	(2.63)	(3.21)	(3.48)	(11.9)	(11.2)
Killing degree days	-6.69	-8.58	-9.18	-31.8	-21.4
	(3.87)	(5.54)	(4.64)	(10.0)	(7.69)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.767	0.752	0.753	0.868	0.868
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

The dependent variable is the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The standard errors are clustered at the state level. The temperature variables are rescaled by the change between the present discounted value of predicted climate change and a 2002 contant climate. The coefficients thus give the impact as a percentage of total land value in the sample in 2002, which is $830 billion. The pooled regression is all census years from 1978 to 2002 contant climate. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "NC" and the "Mean Change" forecast model as "MC".

variable. Their interpretation is straightforward as the dollar impact on land values in 2002. In table 1.9, I multiply these coefficients by the changes in degree days and divide them by the average value of land in the sample to get the percentage impacts.

In line with the theoretical section's discussion on the potential bias, the coefficients on the MC forecasts are larger than the NC forecasts. In contrast to SCD, the combined damages are lower with the MC forecasts than the NC forecasts across specifications as shown in Figure 1.7. The damages are lower because the positive change in the growing degree days impact is higher than the increase of damages arising from killing degree days. Or, said differently, the coefficient of growing degree is biased downwards more heavily than the coefficient of killing degree days, when accounting for the respective changes due to climate change. This confirms that the direction of the bias of total damages is not a-priori clear.

In addition, the killing degree days coefficients for the long differences are larger than the cross-sectional results. The killing degree days coefficient goes up from 0.014-0.015 up to 0.018 and 0.028. Table 1.6 shows the impact this increase has on the damages. The first interpretation of these results is that the omitted variable bias leads to a downward bias in both coefficients. In other words, omitted variables on a county level that are correlated with climate variation lead to an underestimation of the impacts of both growing and killing degree days. The second concern is that the long differences variation is not large enough over time to make farmers change their production practices or change their crop choice. If farmers do not change their practices, then the damages would be higher and the benefits lower as farmers would not use all of their options and the coefficients would be closer to the coefficients that arise using short-run temperature variation. However, this would predict a lower coefficient on growing degree days as farmers cannot capture the full benefits of climate changes. However, the coefficient on growing degree days becomes larger which contradicts this. Another concern is that measurement error puts a downward bias on coefficients in a panel setting (Griliches and Hausman 1986). But if this measurement error is indeed prevalent, then the true coefficients would be even larger in magnitude.

Impacts Across Specifications

I plot the different methods with two forecast specifications in Figure 1.7, whereby I have arranged the models according to the magnitude of the estimated damages. A first observation is that all the point estimates across models are negative, and range from -3.5 percent to -24 percent as a fraction of the current total value of land, or between \$22 and \$203 billion. Second, the standard errors are large and I cannot reject the null hypothesis of no impacts at the 5-percent level for most specifications. Third, the NC-model damages are uniformly smaller than their MC counterparts. While I find that the coefficients on the climate variables are biased downwards, just as SCD, the increase in the growing degree days coefficient outweighs the increase in the killing degree days coefficient when multiplied by their respective path differences. These estimates seem to suggest that the impacts of climate change are negative but often economically quite moderate across specifications.

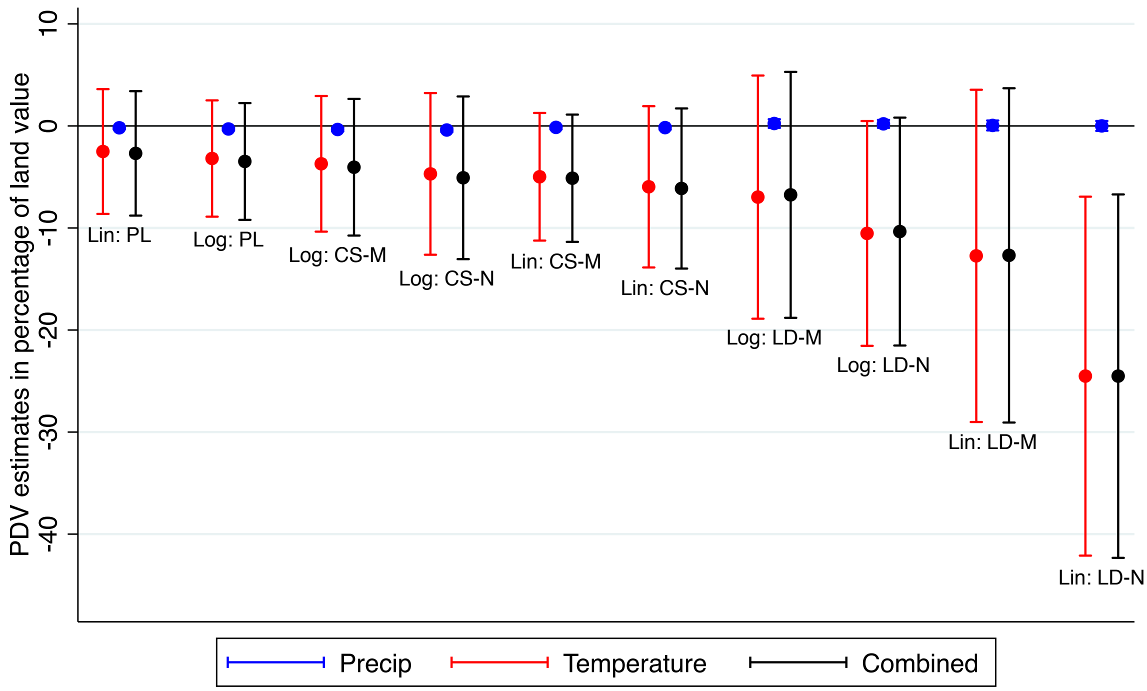

Figure 1.7: PDV Estimates in Percentage of 2002 Land Values

Note: These are present discounted value estimates for different specifications at a 5 percent interest rate. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted mean climate changes and a constant 2002 climate. The estimates are given as a percentage of total land value in the sample in 2002, which is \$830 billion. The red bar denotes the combined impacts of the growing and killing degree days and the blue bar the impacts of precipitation. The regressions include a list of soil variables and quadratic specifications for population density and per capital income. The regressions are weighted by the square root of farmland. The dependent variable is land value or its logarithm as denoted by Lin or Log. The impacts for the logarithm specification are calculated as $100 * (\Delta I\beta - 1)$, where ΔI is the average weighted difference. The impacts for the linear specification are the simple multiplication, divided by the value of land. The pooled regression is denoted by "PL", the 2002 cross-section by "CS" and the long differences specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "N" and the "Mean Change" forecast model as "M". The climate variables are the average of the preceding 30 years. The standard errors are clustered at the state level. The predicted damages come from the multiplication of the coefficients with the mean predicted change across the available climate model scenarios.

These results are much smaller than the main estimates of SCD, who find estimated damages of -$711 billion to -$998.6 billion for a sample of 2,112 counties with a discount rate of 3 percent.[25] On the other hand, my results are much closer to one of their sensitivity checks in which they use ten temperature bins instead of monthly averages. The tenth bin allows to capture extreme temperatures, just as the measure of degree days. With these temperature bins, they find damages from -$58 to -$160 billion.[26] My damages are also in the same range as DG who report damages from $66 billion to $163 billion.[27]

1.5.2 Spatial Analysis: Results by County

The previous results were centered around the impact for the sample as a whole. Yet several papers have pointed out that there could be substantial heterogeneity across counties (SHF; Butler and Huybers 2013). Therefore, I now investigate the impacts on a spatial level across my sample. First, while I use the changes in present discounted value of climate, Figure 1.4 maps out the level changes of counties by 2050. This figure shows that northern counties are set to gain much more growing degree days relative to the south, as well as much fewer killing degree days. These level changes will naturally translate to spatial damages. To analyze spatial damages, I select the cross-sectional regression in 2002 with the MC forecasts. Using this selection, I then calculate estimated impacts for each county, which I display in Figure 1.8 and Figure 1.9.

Figure 1.8 maps out the counties who have negative present discounted impacts from climate change. Figure 1.8 shows that counties located closer to the south are subject to larger losses. These losses arise from the larger increase in killing degree days relative to growing degree days.

25. Another difference is that calculate the damages from 2007 to 2099 and convert them to 2005 dollars.

26. They report damages of $47 to $128 billion but I have rescaled them with their estimated weight to get comparable damage calculations

27. My cross-sectional results provide smaller estimates than their damages, which is expected given the adaptation possibilities over the long-run that are captured within the land value framework.

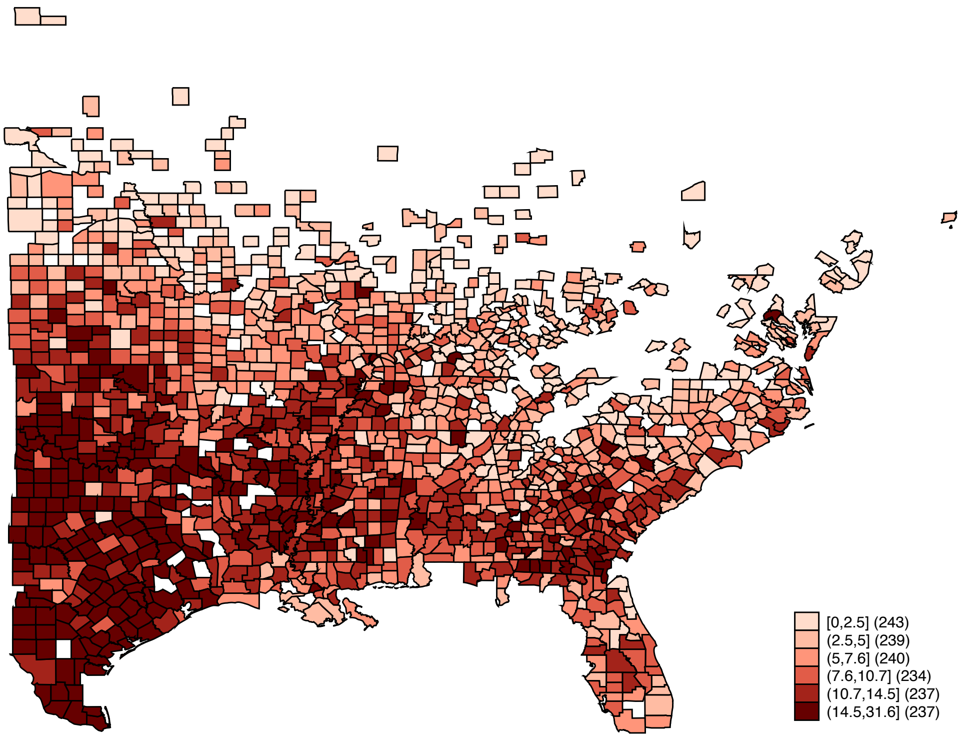

Figure 1.8: Counties with a Negative Present Discounted Value Impact of Climate Change
Note: This figure shows the present discounted damage estimates by county for the "Mean Change" forecast specification with a discount rate of 5 percent and the logarithm of land values as the dependent variable. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted mean climate changes and a constant 2002 climate for that county. The estimates are given as a percentage of the land value in that county in 2002. The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level.

Figure 1.9 displays the counties who have positive present discounted impacts. The farther north a county is located, the higher the probability that there will be estimated benefits from climate change. This result arises from the large increase in growing degree days that some of these northern counties will experience combined with a lower increase of killing degree days.

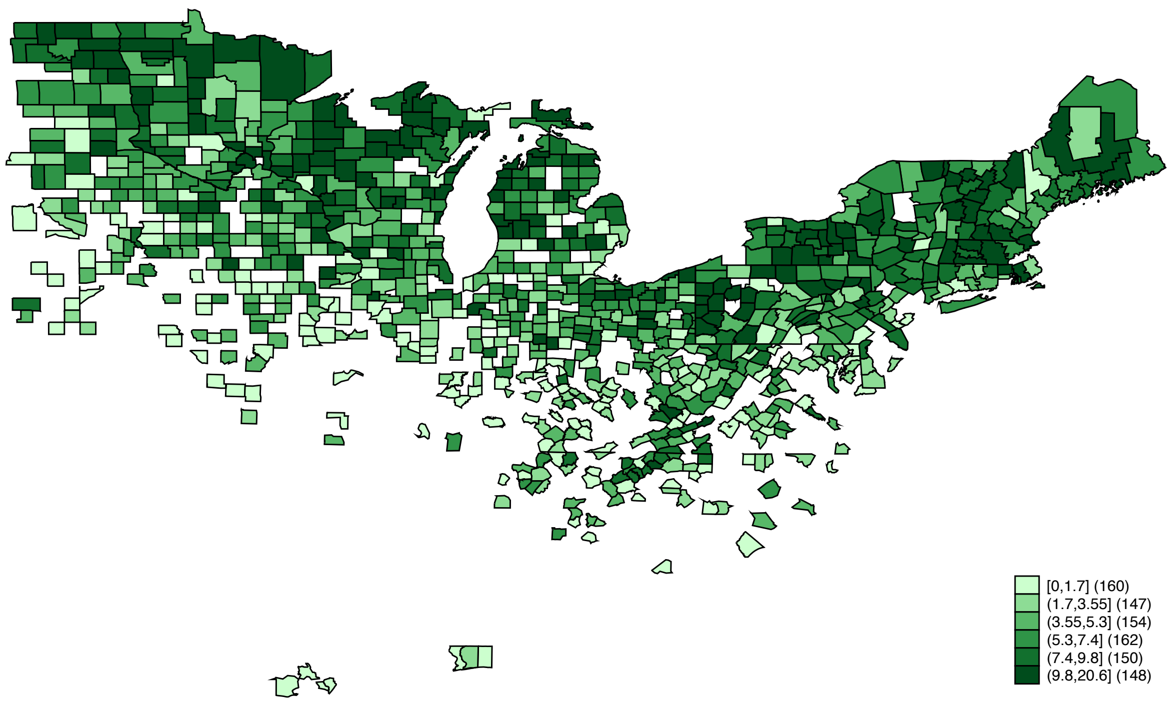

Figure 1.9: Counties with a Positive Present Discounted Value Impact of Climate Change
Note: This figure shows the present discounted benefit estimates by county for the "Mean Change" forecast specification with a discount rate of 5 percent and the logarithm of land values as the dependent variable. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted mean climate changes and a constant 2002 climate for that county. The estimates are given as a percentage of the land value in that county in 2002. The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level.

Table 1.10: Regression Results for Different Farmer Climate Forecasts for the Log-linear Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CS:2002	CS:2002	CS:2002	LD	LD	LD:2002	LD:2002	LD:2002
Growing degree Days	0.0019**	0.0023***	0.0029***	0.00090	0.0043	0.0053**	0.0054**	0.0052**
	(0.00073)	(0.00076)	(0.00078)	(0.0031)	(0.0027)	(0.0025)	(0.0024)	(0.0022)
Killing degree Days	-0.014**	-0.014***	-0.015***	-0.018**	-0.036***	-0.037***	-0.033***	-0.028***
	(0.0056)	(0.0052)	(0.0047)	(0.0085)	(0.0084)	(0.0080)	(0.0068)	(0.0057)
Observations	2340	2340	2340	4680	4680	4680	4680	4680
Adjusted R^2	0.818	0.820	0.819	0.922	0.923	0.924	0.925	0.925
Cluster	State	State	State	State	State	State	State	State
Fixed Effects	St.	St.	St.	St-Yr C.	St-Yr C.	St-Yr C.	St-Yr C.	St-Yr C.
Weight	0	1/2	1	0	1/4	1/2	3/4	1

The dependent variable is the natural logarithm of the value of land per acre. The weight represents the weight put on the "mean-change" forecast relative to the "no-change" forecast. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The coefficients are multiplied by hundred to show the change in percentage in land value from a unit change in the independent variable. The standard errors are clustered at the state level. The pooled regression is all census years from 1978 to 2002. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No-Change" forecast model is denoted by "NC" and the "Mean-Change" forecast model as "MC".

Table 1.11: Regression Results for Different Farmer Climate Forecasts for the Linear Specification

	(1) CS:2002	(2) CS:2002	(3) CS:2002	(4) LD:2002	(5) LD:2002	(6) LD:2002	(7) LD:2002	(8) LD:2002
Growing degree days	0.015	0.020	0.025	0.042	0.071	0.069	0.061	0.053
	(0.019)	(0.019)	(0.020)	(0.068)	(0.066)	(0.067)	(0.066)	(0.065)
Killing degree days	-0.19	-0.19*	-0.20*	-0.69***	-0.80***	-0.70***	-0.57***	-0.46***
	(0.12)	(0.11)	(0.10)	(0.22)	(0.23)	(0.22)	(0.19)	(0.17)
Observations	2340	2340	2340	4680	4680	4680	4680	4680
Adjusted R^2	0.752	0.753	0.753	0.868	0.868	0.869	0.869	0.868
Cluster	State	State	State	State	State	State	State	State
Fixed Effects	St.	St.	St.	St-Yr C.	St-Yr C.	St-Yr C.	St-Yr C.	St-Yr C.
Weight	0	1/2	1	0	1/4	1/2	3/4	1

The dependent variable is the value of land per acre. The weight variable represents the weight put on the "mean-change" forecast relative to the "no-change" forecast. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The standard errors are clustered at the state level. The pooled regression is all census years from 1978 to 2002. The 2002 cross-sectional specification is denoted by "2002" and the long-difference specification from 1978 to 2002 as "LD". The "No-Change" forecast model is denoted by "NC" and the "Mean-Change" forecast model as "MC".

1.5.3 The Importance of Forecasting Models

While the NC and MC forecast model can be analyzed separately, I explore the impact of allowing a weighted combination of these forecasts in more detail. I first analyze what happens when I set different weights between the forecasts and then I report the weight that best fits the data using a non-linear least squares approach as in SCD. For the cross-section results, a first observation is that the damages for each forecast model are very close to each other in magnitude, as was shown in Figure 1.7. The economic bias is therefore much less important in the cross-sectional setting relative to SCD. Table 1.10 and Figure 1.10 show that the coefficients and damages are almost a linear interpolation of the two forecast models. This result is in line with equation 1.12. When I estimate the weight that best fits the data, I find an estimated ω of 0.63 with a standard error of 0.283. This weight is in line with the result of SCD, who find a weight of 0.82 for 2002 (SCD, table 3, column 2(c)). This weight is another confirmation that different forecast models do provide more information rather than a pure NC forecast. In other words, the data support the notion that farmers place a positive weight on future increases in temperature. For the long differences, the situation is more nuanced as the coefficients do not linearly vary between the two bounds, nor do the damages. Equation 1.13 shows that the bias is dependent on more factors, and these factors might be correlated with the other covariates. For the linear specification, the damages go down for the 25 percent weight to then increase towards the pure mean-change forecast damages. For the logarithm specification, I find that the pattern is similar, although the 50 percent weight has a similar damage as the 0 percent weight.

Using a non-linear least squares approach, I can estimate the weight that best fits the data for the long differences approaches. For the logarithm and linear specification, this approach suggests weights of 0.63 and 0.72 with standard errors of 0.1653 and 0.1153. These estimates suggest the long differences specification with NC forecasts would overestimate the damages in the linear case and only slightly in the logarithm case. These estimated weights are again in line with the results of SCD.

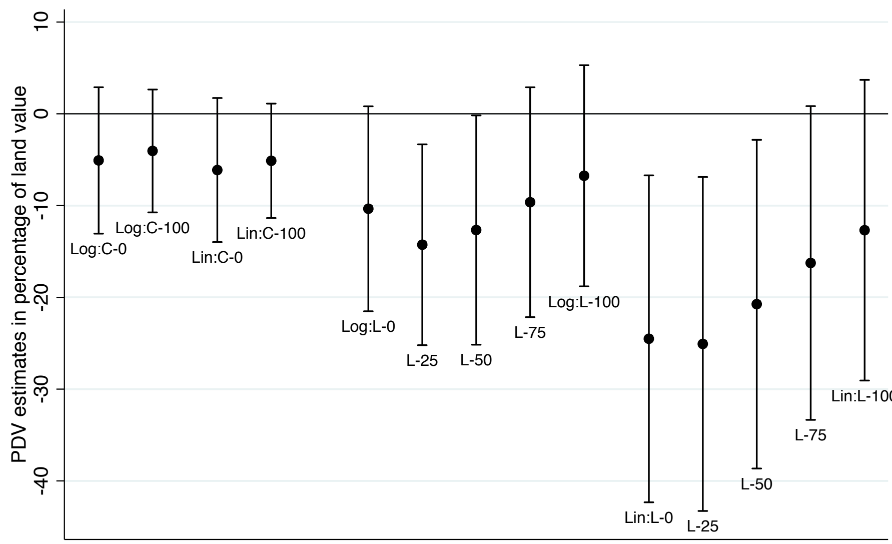

Figure 1.10: PDV Estimates for Different Combinations of Forecast Models

Note: These are present discounted value estimates for different specifications at a 5 percent interest rate, with varying weights on forecast models. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted mean climate changes and a constant 2002 climate. The estimates are given as a percentage of total land value in the sample in 2002, which is $830 billion. The regressions include a list of soil variables and quadratic specifications for population density and per capital income. The regressions are weighted by the square root of farmland. The dependent variable is land value or its logarithm as denoted by "Lin" or "Log". The impacts for the logarithm specification are calculated as $100 * (\Delta I\beta - 1)$, where ΔI is the farmland-weighted average difference. The impacts for the linear specification are the simple multiplication, divided by the value of land. The pooled regression is denoted by "PL", the 2002 cross-section by "C" and the long differences specification from 1978 to 2002 as "L". The weights go from a 0 to 100 percent, and goes from 0 for the "No Change" forecast model up to 100 for the "Mean-Forecast" model. The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level.

1.5.4 The Impact of the Choice of Climate Model on Estimated Damages

Figure 1.11 captures graphically the impact of the choice of climate model on the estimated damages. In order to estimate these impacts, I calculate the present discounted value of the growing and killing degree day variables for each of the climate models with a 5 percent discount rate. For the NC model, this has no impact as the predicted climate is constant. In the last step, I multiply the coefficients by the implied growing and killing degree day differences for each climate model relative to a no-change scenario. I find that the choice of climate model can have important impacts on the estimated damages as the damages vary between 0 and 20 percent for most specifications, or from $0 to $166 billion. Only the long differences specification with NC forecasts has a much larger range, even going up to 50 percent of total land value for one climate model. This larger range is the result of the much higher killing degree days coefficient from the regression, which gets multiplied by the higher killing degree days differences of some climate models.

This 20 percentage point range is as large or larger than the uncertainty from the regression and the variation across the estimated impact from different specifications. Therefore, these results confirm the findings of Burke et al. (2015) that choosing only one or two climate models might underestimate the range of estimates substantially.

1.5.5 The Impact of the Choice of Discount Rate on Estimated Damages

So far, I have estimated the impacts using a 5 percent discount rate. As a next sensitivity analysis, I vary the discount rate and analyze the impacts on the estimates, which are displayed in Figure 1.12. For each specification, I recompute the present discounted variables of climate for the discount rates of 3, 5 and 8 percent. For the NC forecasts, this leads to a simple rescaling. I then multiply these new coefficients by the difference between the recomputed present discounted climate variables.

It is natural to expect that a lower distinct rate will lead to larger present discounted value estimates. I indeed find that the damages with a 3 percent discount rate are on average larger

Figure 1.11: PDV Estimates for Different Climate Models

Note: These are present discounted value estimates for different climate models and specifications for a 5 percent interest rate. Each dot represents a climate model. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted climate changes of the model and a constant 2002 climate. The estimates are given as a percentage of total land value in the sample in 2002, which is $830 billion. The regressions include a list of soil variables and quadratic specifications for population density and per capital income. The regressions are weighted by the square root of farmland. The dependent variable is land value or its logarithm as denoted by "Ln" or "Lg". The impacts for the logarithm specification are calculated as $100 * (\Delta I \beta - 1)$, where ΔI is the farmland-weighted average difference. The impacts for the linear specification are the simple multiplication, divided by the value of land. The pooled regression is denoted by "PL", the 2002 cross-section by "CS" and the long differences specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "N" and the "Mean-Forecast" model as "M". The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level.

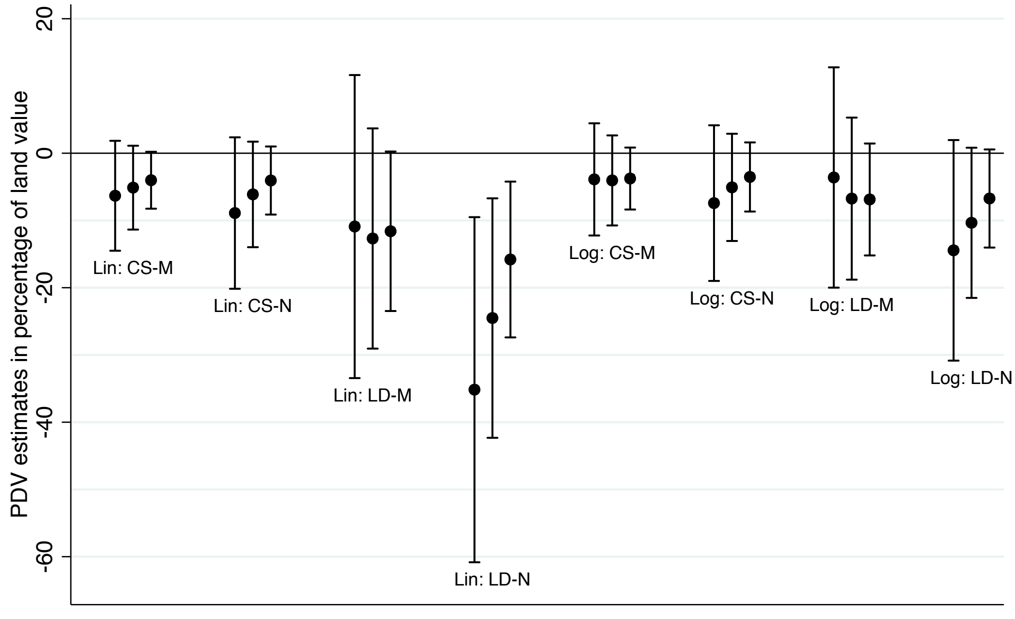

Figure 1.12: PDV Estimates Using Different Discount Rates

Note: These are present discounted value estimates for different specifications and discount rates of 3, 5 and eight percent. The discount rates are displayed in this order, going from 3 to eight percent for each specification. The estimates are calculated as the multiplication of the coefficients with the difference between the present discounted value of the predicted mean climate changes and a constant 2002 climate. The estimates are given as a percentage of total land value in the sample in 2002, which is $830 billion. The regressions include a list of soil variables and quadratic specifications for population density and per capital income. The regressions are weighted by the square root of farmland. The dependent variable is land value or its logarithm as denoted by Lin or Log. The impacts for the logarithm specification are calculated as $100*(\Delta I\beta - 1)$, where ΔI is the farmland-weighted average difference. The dependent variable is land value or its logarithm as denoted by "Lin" or "Log". The 2002 cross-section specification is denoted by "CS" and the long differences specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "N" and the "Mean-Forecast" model as "M". The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level.

than those with a 5 percent discount rate. However, this result does not hold for the long differences specification with MC forecasts, where the damages with the 3 percent discount rate are slightly lower due to a much lower killing degree day coefficient.

1.5.6 Robustness to Regression Specification and Sample Selection

To probe the robustness of these results, I now examine a range of other regression specifications. Table 1.12 and 1.13 explore the robustness when I do not weight by farmland. I find that the estimates in absolute magnitude increase for both growing and killing degree days.

Table 1.12: Regression Results with Different Weights for the Log-linear Specification

	(1) NC:2002	(2) MC:2002	(3) NC:2002-NW	(4) MC:2002-NW
Growing degree days	5.53	8.49	5.91	8.32
	(2.11)	(2.31)	(2.18)	(2.33)
Killing degree days	-10.3	-12.3	-19.1	-18.1
	(4.30)	(3.80)	(7.36)	(5.50)
Observations	2340	2340	2340	2340
Adjusted R^2	0.818	0.820	0.804	0.806
Cluster	State	State	State	State
Fixed Effects	St.	St.	St.	St.

This table analyzes the sensitivity of the results to the use of farmland weights. The regressions that are not weighted by the square root of farmland acres are denoted by "NW". The dependent variable is the value of land per acre. Otherwise, the regressions are identical to table 1.8.

Table 1.13: Regression Results with Different Weights

	(1) NC:2002	(2) MC:2002	(3) NC:2002-NW	(4) MC:2002-NW
Growing degree days	2.61	4.57	3.95	6.24
	(3.21)	(3.57)	(4.19)	(4.65)
Killing degree days	-8.57	-9.56	-22.5	-20.5
	(5.53)	(4.75)	(9.43)	(7.47)
Observations	2340	2340	2340	2340
Adjusted R^2	0.752	0.753	0.744	0.745
Cluster	State	State	State	State
Fixed Effects	St.	St.	St.	St.

This table analyzes the sensitivity of the results to the use of farmland weights. The regressions that are not weighted by the square root of farmland acres are denoted by "NW". The dependent variable is the value of land per acre. Otherwise, the regressions are identical to table 1.9.

Though I find that the impact of killing degree days goes up relatively more, as demonstrated in table 1.12. Similarly, tables 1.14 and 1.15 explore the sensitivity of results to the exclusion of state fixed effects. The original paper by MNS did not include state fixed effects. If state fixed effects are omitted, the benefit is that the range of the support increases. The downside is that the potential for omitted variable bias goes up. In addition, Fisher et al. (2012) point out that there could be other state-specific factors like crop-specific subsidies or differential price changes that could bias the results. When I omit state fixed effects, I again find slightly larger coefficients which add up to slightly higher damages for the specifications.

Table 1.14: Regression Results with Different Fixed Effect Specifications for the Log-linear Specification

	(1) NC:2002	(2) MC:2002	(3) NC:2002	(4) MC:2002
Growing degree days	5.53	8.49	8.54	12.1
	(2.11)	(2.31)	(3.69)	(4.02)
Killing degree days	-10.3	-12.3	-21.4	-21.6
	(4.30)	(3.80)	(9.35)	(7.58)
Observations	2340	2340	2340	2340
Adjusted R^2	0.818	0.820	0.665	0.682
Cluster	State	State	State	State
Fixed Effects	St.	St.	-	-

The dependent variable is the natural logarithm of the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The standard errors are clustered at the state level. The temperature variables are rescaled by the average weighted change between the present discounted value of predicted climate change and a 2002 contant climate. The 2002 cross-sectional specification is denoted by "2002" and the long differences specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "NC" and the "Mean Change" forecast model as "MC".

I also test the impact of excluding the socio-economic variables. To do so, I first omit the per capita income variable for both cross-sectional regressions in 2002. Second, I exclude both the per capita income and population density variables. Tables 1.16 and 1.17 display those impacts. I find that the benefits of growing degree days stay constant when per capita income is excluded, and go up by four percentage points when both socio-economic variables

Table 1.15: Regression Results with Different Fixed Effect Specifications

	(1) NC:2002	(2) MC:2002	(3) NC:2002	(4) MC:2002
Growing degree days	2.61	4.57	6.53	9.36
	(3.21)	(3.57)	(3.53)	(3.75)
Killing degree days	-8.57	-9.56	-19.4	-19.2
	(5.53)	(4.75)	(7.60)	(6.14)
Observations	2340	2340	2340	2340
Adjusted R^2	0.752	0.753	0.616	0.625
Cluster	State	State	State	State
Fixed Effects	St.	St.	-	-

The dependent variable is the value of land per acre. The regressions include a list of soil variables and quadratic specifications for population density and per capital income and are weighted by the square root of farmland. The PDV climate variables are calculated with an interest rate of 5% and the mean climate predictions across climate models. The standard errors are clustered at the state level. The temperature variables are rescaled by the average weighted change between the present discounted value of predicted climate change and a 2002 contant climate. The 2002 cross-sectional specification is denoted by "2002" and the long differences specification from 1978 to 2002 as "LD". The "No Change" forecast model is denoted by "NC" and the "Mean Change" forecast model as "MC".

are dropped. The impacts of a killing degree day goes up by 3 percentage points when per capita income is excluded, and about seven percentage points when both socio-economic variables are dropped. Combined, these effects lead to an average increase in damages of 3 percentage points. A similar pattern holds in table 1.17 for the linear specification, where the slight increase in growing degree day coefficient this time almost fully offsets the lower killing degree day coefficient.

Besides the robustness of the results to variable selection, I also explore the impact of interactions among the temperature variables. To explore this, I create three climate zones based on the sorted levels of growing degree days. These climate regions, which could be labeled “cold”, “moderate”, and “warm” climate regions also correspond to the north, middle, and south regions in my sample. I create these regions based on equal sized bins, going from cold to hottest. I then interact both the growing and killing degree day variables with these climate regions. Table 1.18 shows these results for the different specifications, again with a 5 percent discount rate. I find that there is indeed variation across regions to

Table 1.16: Regression Results with Varying Socio-Economic Specifications for the Log-linear Specification

	(1) NC:2002	(2) MC:2002	(3) NC:2002-R	(4) MC:2002-R	(5) NC:2002-RP	(6) MC:2002-RP
Growing degree days	5.53	8.49	5.84	9.07	9.01	12.6
	(2.11)	(2.31)	(2.18)	(2.42)	(2.94)	(3.17)
Killing degree days	-10.3	-12.3	-13.2	-14.8	-17.6	-18.4
	(4.30)	(3.80)	(4.51)	(4.08)	(6.25)	(5.51)
Observations	2340	2340	2340	2340	2340	2340
Adjusted R^2	0.818	0.820	0.803	0.806	0.742	0.747
Cluster	State	State	State	State	State	State
Fixed Effects	St.	St.	St.	St.	St.	St.

This table analyzes the sensitivity of the results to the choice of socio-economic variables. The regression with "NR" excludes the per capita income, while "RP" excludes both per capita income and population density. The dependent variable is natural logarithm of the value of land per acre. Otherwise, the regressions are identical to table 1.8.

Table 1.17: Regression Results with Varying Socio-Economic Specifications

	(1) NC:2002	(2) MC:2002	(3) NC:2002-R	(4) MC:2002-R	(5) NC:2002-RP	(6) MC:2002-RP
Growing degree days	2.61	4.57	2.77	4.88	7.59	10.3
	(3.21)	(3.57)	(3.37)	(3.74)	(5.01)	(5.49)
Killing degree days	-8.57	-9.56	-10.3	-11.0	-16.9	-16.6
	(5.53)	(4.75)	(5.46)	(4.73)	(8.86)	(7.60)
Observations	2340	2340	2340	2340	2340	2340
Adjusted R^2	0.752	0.753	0.722	0.724	0.592	0.596
Cluster	State	State	State	State	State	State
Fixed Effects	St.	St.	St.	St.	St.	St.

This table analyzes the sensitivity of the results to the choice of socio-economic variables. The regression with "NR" excludes the per capita income, while "RP" excludes both per capita income and population density. The dependent variable is the value of land per acre. Otherwise, the regressions are identical to table 1.9.

both growing and killing degree days. The colder climate region displays a higher sensitivity to both growing and killing degree days across all specifications. This sensitivity goes down for growing degree days, albeit modestly. On the other hand, the impact of a killing degree day decreases more strongly by climate region. These results could arise from a variety of different adaptations from farmers, such as choosing crops that thrive at higher temperatures, changing seeds, or production practices.

Table 1.18: Regression Results Explaining Farmland Value per Acre

	(1)	(2)	(3)	(4)	(5)
	NC:Pooled	NC:2002	MC:2002	NC:LD	MC:LD
T1 × Growing degree days	0.0059***	0.0056***	0.0071***	0.0040*	0.0060***
	(0.00065)	(0.00073)	(0.00090)	(0.0021)	(0.0018)
T2 × Growing degree days	0.0053***	0.0049***	0.0064***	0.0053	0.0077
	(0.00057)	(0.00065)	(0.00078)	(0.0058)	(0.0048)
T3 × Growing degree days	0.0047***	0.0043***	0.0056***	-0.0093	0.0026
	(0.00057)	(0.00065)	(0.00076)	(0.0090)	(0.0047)
T1 × Killing degree days	-0.082***	-0.097***	-0.079***	-0.0031	-0.027*
	(0.013)	(0.015)	(0.012)	(0.033)	(0.014)
T2 × Killing degree days	-0.042***	-0.043***	-0.041***	-0.050**	-0.025
	(0.0050)	(0.0049)	(0.0038)	(0.020)	(0.020)
T3 × Killing degree days	-0.016***	-0.017***	-0.019***	0.00099	-0.026***
	(0.0025)	(0.0045)	(0.0035)	(0.015)	(0.0065)
Observations	14040	2340	2340	4680	4680
Adjusted R^2	0.825	0.831	0.833	0.923	0.926
Cluster	State	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.	St-Yr C.

This table analyzes the sensivity of the coefficients to different climate regions. The climate regions are defined as groups from cold to warm with an equal number of observations in each group. The dependent variable is natural logarithm of the value of land per acre. Otherwise, the regressions are identitical to table 1.6.

1.5.7 Results for Damages in 2050

In this section, I repeat the exercise to analyze the impacts of climate change by 2050 for a constant level shift as in SHF, as is the normal procedure in the literature. For this exercise, I use the Hadley model (HadCM3 A1B), which is the model SHF use to predict damages.

While I will compare the results, there are differences in the set-up. Besides a small difference in sample size, there are differences between their covariates and mine. First, SHF include latitude in their regression. Second, they utilize growing degree days from 8 to 32 °C, which they include with a squared term, and the squared roots of the degree days above 34 °C. Third, I utilize the more expansive set of soil variables from MNS. Fourth, SHF do not report estimates when weighting by farmland, though they report their estimates are similar (SHF, 117, footnote 11). With these caveats in mind, SHF find damages from -20.6 percent for the B2 scenario and -20.21 percent A2 scenario.

Table 1.19: Regression Results Explaining Farmland Value per Acre in 2050 for the Log-linear Specification

	(1) CS:Pooled	(2) CS:2002	(3) CS:Pooled	(4) LD:78-02
Growing Degree Days	0.051***	0.037**	0.046**	0.026
	(0.015)	(0.015)	(0.017)	(0.064)
Killing Degree Days	-0.27***	-0.25*	-0.30***	-0.39**
	(0.082)	(0.13)	(0.077)	(0.17)
Observations	14040	2340	14040	4680
Adjusted R^2	0.812	0.820	0.638	0.922
Cluster	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.

The dependent variable is natural logarithm of the value of land per acre. The coefficients are multiplied by 100 to give the percentage impact on land values of a permanent change in the independent variable.

Table 1.20: Regression Results Explaining Farmland Value per Acre in 2050

	(1) CS:Pooled	(2) CS:2002	(3) CS:Pooled	(4) LD:78-02
Growing Degree Days	0.48	0.26	0.46	1.00
	(0.31)	(0.39)	(0.33)	(1.46)
Killing Degree Days	-2.93	-3.53	-3.84**	-14.4***
	(1.84)	(2.73)	(1.49)	(4.65)
Observations	14040	2340	14040	4680
Adjusted R^2	0.766	0.752	0.586	0.867
Cluster	State	State	State	State
Fixed Effects	St-Yr.	St.	St.	St-Yr C.

The dependent variable is the value of land per acre. The coefficients are multiplied by 100 to give the percentage impact on land values of a permanent change in the independent variable.

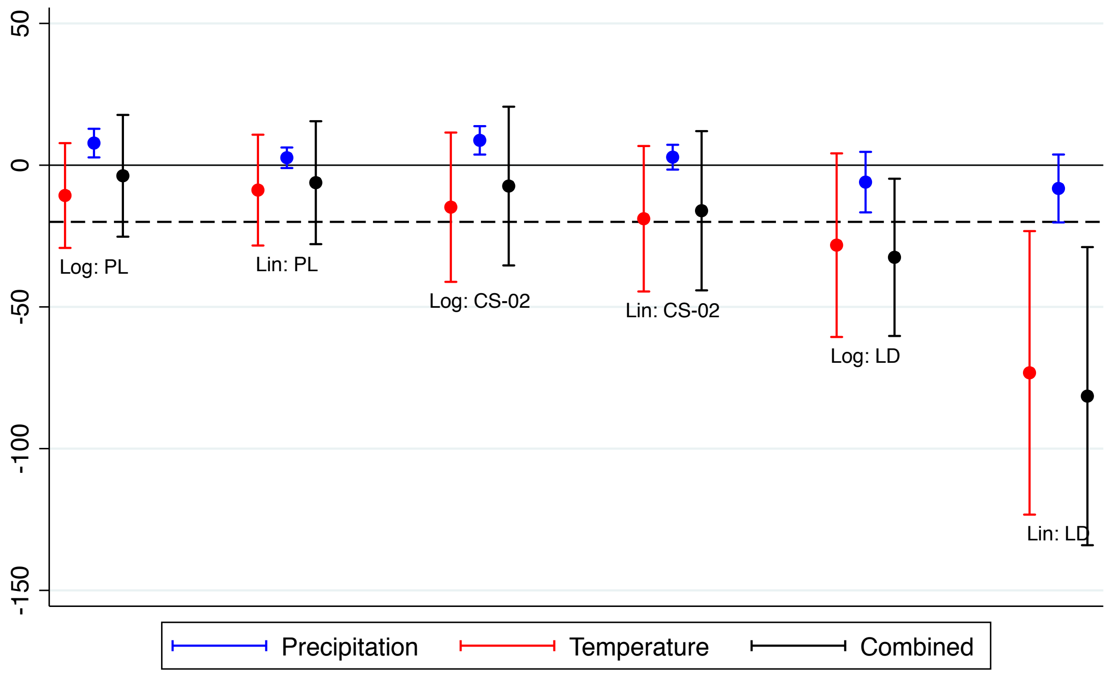

Figure 1.13: Damage Estimates by 2050

Note: These are the estimates of the damages by 2050 as a percentage of total land value in the sample. The regressions include a list of soil variables and quadratic specifications for population density and per capital income. The dependent variable is land value or its logarithm as denoted by Lin or Log. The climate variables are the average of growing degree days in the preceding 30 years. The standard errors are clustered at the state level. The predicted damages come from the multiplication the coefficients with the predicted change according to each of the available climate model scenarios. The point magnitudes for the logarithm specification are computed as $100 * (\Delta C\beta - 1)$ where ΔC are the average climate changes. As a result, the confidence intervals are asymmetric. ΔC is computed as the farmland-weighted change in climate variables.

Tables 1.19 and 1.20 show the regression coefficients. In Figure 1.13, I display the combined impacts. Figure 1.13 shows that estimated impacts using the coefficients of the cross-sectional specification in 2002 range from -7.4 percent for the logarithm specification and -16 percent for the linear specification. The results for the pooled regression are smaller, though I am using state-by-year fixed effects, whereas SHF average the census years and then include state fixed effects. The results for the long differences are again larger at -32.5 percent. The largest predicted damages are for the linear long differences specification with estimated damages of -81 percent. In addition, the damages from temperature are similar to in magnitude to SHF. While the damages in SHF come nearly all from the degree days above 34 °C, precipitation and growing degree days play a minimal role. In contrast, I do find significant gains from the increase in growing degree days as well as significant impacts from precipitation.

1.6 Conclusion

In this paper, I estimate the impacts of climate change on agricultural land values using a variety of methods and forecast models. First, I combine a framework that incorporates different farmer forecasts of future climate with degree days. These degree days allow me to capture the impacts of extreme temperatures. I then use this framework to estimate the damages of predicted climate changes relative to a constant 2002 climate. Besides the cross-sectional land values regression, I exploit climate variation over time between 1978 and 2002 within counties. Using this variation, I address the potential time-invariant omitted-variable bias of a cross-sectional regression. Furthermore, I estimate the impacts using a range of climate models.

The present discounted damages range from \$22 to \$200 billion in 2002 dollars, with a mean of \$67 billion dollars using a discount rate of 5 percent. In addition, I find that the estimates using the long-run climate variation are on average \$64 billion larger than the cross-sectional regressions. Furthermore, the choice of climate model has significant economic importance as the estimates across climate models vary about \$200 billion for nearly all specifications. There is also substantial heterogeneity in impacts across counties as some counties benefit while other counties have large estimated damages.

CHAPTER 2

ADAPTATION TO CLIMATE CHANGE: EVIDENCE FROM CROP CHOICE IN AGRICULTURE

2.1 Introduction

[1]The previous chapter dealt with estimating the overall impacts of climate change through the use of land values. The strength of using land values is that this approach theoretically incorporates all adaptation possibilities. The drawback of using land values is that this does not allow to analyze the underlying adaptation patterns or mechanisms.

In recent years, the question of adaptation has taken up a central place in the climate change literature (Aufhammer and Schlenker 2014). The importance of adaptation possibilities has come to the forefront of research as yields are expected to be impacted severely. For example, Schlenker and Roberts (2009) estimate that US yields for corn, soybeans, and cotton will decrease by 63-82 percent by the end of the century. However, this crucial question of adaptation in agriculture has been challenging to analyze because it requires substantial information on both the decisions with and without adaptation.

In this paper, we tackle this important question by analyzing how much can farmers mitigate the costs of climate change by altering their crop planting decisions. We analyze these planting decisions through the use of a discrete choice model, which we combine with a comprehensive data set on insurance costs. Leveraging this combination allows us to estimate the parameters of the profit function. Therefore, we can construct measures of costs and benefit to farmers from changes in temperature or precipitation relative to the other uses of land. In addition, we can predict changes in crop shares due to climate changes as well as the adaptation gains from these changes.

1. This paper is joint work with Michael Greenstone and Ishan Nath. This paper has benefited from conversations with Amir Jina, Robert Rosner, Steve Cicala, Robert H. Topel, Els De Brabander, Stephen Denuyl, Joonhwi Joo, Jack Mountjoy, Oliver Browne, and seminar participants at the microeconomics lunch at the University of Chicago, and the energy and environment EPIC lunch. We thank Michael Galperin and Henry Zhang for excellent research assistance.

Using this framework, we analyze two different choice sets. In our first choice set, we focus on corn and soybeans relative to other options. Because corn and soybeans are extensively grown in multiple states, these crops have the highest numbers of counties with available insurance prices. In addition, these crops have been the central focus of an extensive literature that focuses on yield-losses from temperature or climate changes (Aufhammer and Schlenker 2014). In the second choice set, we include additional crops based on insurance availability. To address selection effects, we use a two-step procedure based on Heckman (1979) and Hortasu and Joonhwi (2015).[2] In the first choice set, we find that farmers are more likely to grow both corn and soybeans on land with more growing degree days (GDD) and fewer killing degree days (KDD). Farmers are less likely to grow corn and soybeans when insurance costs are higher. Farmers are willing to pay 1.4 cents per GDD and -17.9 cents per KDD on land growing corn, and 1.6 cents per GDD and -18.6 cents per KDD on land growing soybeans. In the second choice set, farmers who grow corn are willing to pay up to 2.5 cents for beneficial temperatures depending on the specification, while they are willing to pay and 32.3 cents to avoid an increase in extreme temperatures.

Using these results, we find that climate change will produce a severe reduction in the share of land used to grow corn and soybeans by the middle of the century. When farmers are allowed to re-optimize their land use, climate damages in 2050 are \$8.9 to \$11.8 billion lower compared to a scenario where their choice of crops is held constant. This range of damages varies according to the predictions of different climate scenarios.

The closest papers to ours are Costinot et al. (2016), Kurukulasuriya and Mendelsohn (2008), Seo and Mendelsohn (2008), Scott (2013), Kalouptsidi et al. (2015), and Anderson et al. (2012). Kurukulasuriya and Mendelsohn (2008), Seo and Mendelsohn (2008), and Anderson et al. (2012) predict crop choice patterns but do not estimate the economic gains of these substitution patterns. Scott (2013) and Kalouptsidi et al. (2015) analyze

2. For this exercise, we include barley, corn, cotton, flaxseed, oats, potatoes, sorghum, soybeans, rice, sugar beets, sunflower, and wheat.

the responsiveness of cropland along the extensive margin but do not identify the economic gains from switching among crops. Costinot et al. (2016) develop a structural model based on a competitive model of trade. In contrast, we leverage a discrete choice model which we combine with data on the costs of insurance. To the best of our knowledge, we are the first to leverage a discrete choice framework in an agricultural setting that allows us to recover the economic value of adapting to climate change through crop planting decisions.

While we can investigate one of the primary adaptations of farmers, our discrete choice approach also has several limitations. First, as we estimate the model on cross-sectional data, we can only analyze substitution patterns at current technology. However, this limitation is inherent in nearly all models used in the literature. Second, our approach does not account for price-effects. While these price effects are important and have already been analyzed in different contexts (Costinot et al. 2016) ours is the first to provide empirical estimates of the upper bound of the magnitude. Third, we abstract away from adaptation costs as we are investigating about long-run changes. Mendelsohn et al. (1994) argue that these adaptation costs are likely to be small due to the long time horizon and rapid turnover of the capital stock in agriculture. Fourth, we use the cross-section to identify the impacts. Thus our estimation cannot entirely overcome the omitted variable bias arising from unobserved fixed county variables that are correlated with the error term.[3]

The remainder of the paper is as follows. In section 2.2, we set up a conceptual framework for adaptation in agriculture. Section 2.3 covers the data and illustrates the variability in climate data. Section 2.4 discusses the model and econometric strategy. Section 2.5 contains the results, while section 2.6 concludes.

3. We control for an extensive set of covariates and weather variables to alleviate this problem. Moreover, we focus on the crop choice of farmers, and not the value of land, which is determined by a much wider array of factors. We are also currently exploring extensions of this paper into a panel setting that would alleviate some of these concerns.

2.2 Conceptual Framework

In this section, we set up a conceptual framework to interpret the gains from adaptation. To start, suppose a profit-maximizing farmer chooses which crop to grow on a plot i. Each plot has a specific temperature T, rainfall R, and soil S. The farmer chooses inputs I. Each crop has a price vector, P, for related inputs and outputs. The farmer's profits from choosing to plant corn are given by:

$$\pi_{corn}(I|T, R, S, P). \tag{2.1}$$

Temperature affects both revenues and costs. The farmer's profits from choosing to plant soy are given by:

$$\pi_{soybeans}(I|T, R, S, P). \tag{2.2}$$

The farmer also has a potential profit function for the outside crop or non-crop options that are a function of these same variables.

Figure 2.1 displays the different possibilities for a farmer to adapt. Assume climate is in a long-run steady state at T_1. At this point, both the long-run and short-run profits will be equal. If the climate changes from T_1 to T_2, the farmer will have several substitution possibilities depending on the time horizon. In the short run, a farmer who stays with the same crop will suffer damages along the dotted line. However, given a longer time horizon, the farmer can change his seeds or production practices for a given crop. The farmer will thus move along the long-run line for crop 1 and move to point B_2. Burke and Emerick (2016) analyze the impacts of changes in temperatures and climate for corn and soybeans and find that farmers are limited in their adaptation responses within crops. Thus, the distance between the short and long-run curve for a given crop would be small. However, in this paper, we aim to analyze the difference between the long-run of crop 1 and the long-run profits of crop 2. Given changes in climate, a farmer's primary mode of adapting might be to

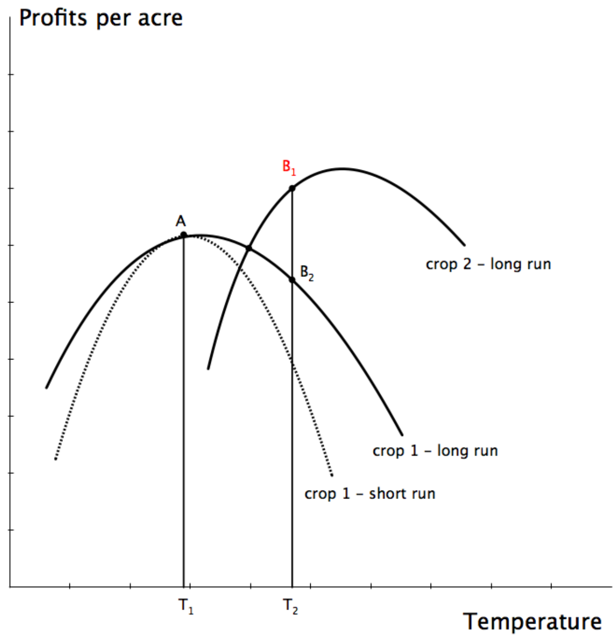

Figure 2.1: Conceptualizing Adaptation to Climate Change

switch crops. For example, as the northern parts of the US are expected to become warmer, we would expect a northern movement of crops.

An important conceptual and empirical point is graphically presented in figure 2.1. This figure shows that the profits of farmers overall, relative to the starting point, might go up or down based on the level of crop 2's long-run profit. In figure 2.2, B_1 is above A in the first figure and below A in the second. Farmers might thus gain from climate change as well as lose. This point could be very relevant to farmers in Canada, as crops are set to migrate north. If temperatures increase in Canada, farmers might grow more higher-value crops wheat, corn, and soybeans in those regions, which would lead to an overall gain.

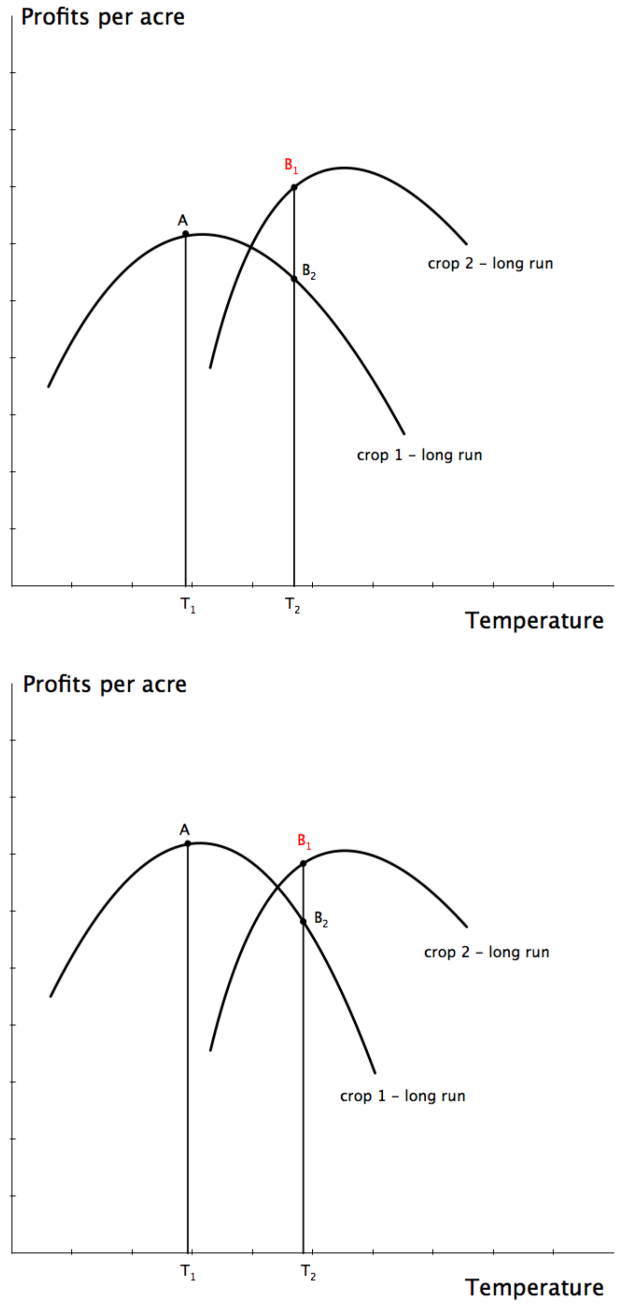

Figure 2.2: Conceptualizing Adaptation from Crop Choice

In order to estimate the damages from climate change, several approaches have been developed, each with its own assumptions for adaptation possibilities. A first approach is a hedonic approach, whereby cross-sectional variation in average weather variables is used to estimate the impacts (Mendelsohn et al. 1994; Schlenker et al.2005). This approach theoretically incorporates all adaptation possibilities, but it cannot identify how much farmers have mitigated through adaptation. A second approach is the panel literature that analyzes yields or profits. The panel literature approach uses random weather variation across years to estimate the impacts on yields or profits, relative to their trend (Deschnes and Greenstone 2007; Roberts and Schlenker 2009; Dell et al. 2012; Moore and Lobell 2014 Lobell et al. 2011; Deschnes and Greenstone 2011). The strength of this approach is that the identification is strong. The drawback is that only short-run changes can be analyzed. Furthermore, by analyzing one crop at a time, this literature cannot incorporate switching among crops. A third approach is to use a structural model based on a competitive model of trade (Costinot et al. . In our approach, we use a discrete choice model which we combine with data on the costs of insurance.

In section 2.4, we demonstrate how we use a discrete choice logit mode to set up a cross-sectional county-level crop share regression. We then estimate the coefficients on temperature and money, controlling for soil quality, precipitation, and irrigation. These estimates allow us to calculate willingness to pay (WTP) measures for changes in climate. This WTP measure for a change in climate, for a given crop, is relative to the outside option. This WTP measure can be calculated as the ratio of the coefficients on climate and insurance costs. We can thus estimate the impact of an increase in temperature on the share of a crop in a country. In other words, this method uses differences in climate across counties to estimate the effects of changes of climate within a county. After we obtain these estimates, we can extrapolate to the years 2070-2099 to see how farmers will change their crop choice as a result of changing temperatures. In this section, we explain the econometric strategy in detail. The damages, relative to the outside good can then be written as

$$\sum_{j \epsilon J} WTP * \Delta Climate * Acres_j. \tag{2.3}$$

Using this formula, we can calculate changes in agricultural profits due to climate change under two scenarios, both when we hold the current crop choice fixed and when we allow farmers to fully optimize across all crops.

2.3 Data Sources and Summary Statistics

2.3.1 Crop and Soil Data

Our crop data comes from the USDA Census of Agriculture. The USDA publishes county-level data on harvested acres of corn, soybeans and other crops in a county for every census year. We use the census years of 1997, 2002, and 2007. We use two different soil datasets for our estimations. First, we use a soil dataset from MNS, who constructed this dataset from the National Resource Inventory (NRI).[4] The NRI surveys approximately 800,000 sites to obtain soil samples and land characteristics. This survey occurs during census years. County-level data are then obtained by taking a weighted average across the nearest sites of the NRI survey. We use the fraction of irrigated land, the fraction of flood-prone acres in a county, soil erosion (K-factor), the slope length, the fraction of sand and clay, permeability, moisture capacity, and the salinity of the soil in a county. For irrigation, we use the irrigated share of harvested cropland. Our second soil dataset comes from the SSURGO database, a database developed by the USDA-NRCS. We employ this second dataset for our results with multiple crops.[5]

4. http:// www.nrcs.usda.gov/technical/NRI/

5. In future work, this will allow us to predict the impacts of climate change for regions in Canada.

2.3.2 Climate Data

In this paper, we use the agronomic concept of "degree days." Degree days, which represent heating units, have become a standard way to measure temperature in the agronomy literature (see Schlenker, Hanemann and Schlenker 2006; Deschnes and Greenstone 2007). Degree days capture the cumulative exposure of crops to specific temperature ranges. Therefore, degree days can capture the exposure to extreme temperatures that are missed by average monthly temperatures. For example, Schlenker and Roberts (2009) analyze the impact of temperature on corn, soybeans, and cotton, using a panel data approach. Using degree days, they compare a flexible polynomial approach, an approach with bins, and a piecewise-linear function. They document that the piecewise linear-function performs nearly as well as the fully flexible polynomial fit. In addition, they find that the impacts follow a linear form for corn, cotton, and soybeans, with a threshold for each crop at 29, 20 and 32 °C. We use temperature data from the Berkeley Earth Surface Temperature (BEST) from which we calculate degree days for the growing season from April 1 to end of September. We follow Burke and Emerick (2016) and use thresholds from 0 to 29 °C and 0 to 30 °C. Precipitation data are obtained from the University of Delaware.[6] Climate change projections are calculated for the RCP 4.5 and 8.5 scenarios for the ACCESS (Australian Climate Change Earth System Simulator) climate model.

2.3.3 Insurance Data

Background on Crop Insurance

In 1938, the Federal Crop Insurance Company (FCIC) was created to provide insurance for farmers. After initial heavy losses due to severe weather conditions, the insurance program was adjusted to very moderate in scope (Coble et al. 2010). In 1980, the Federal Crop

6. Willmott, C. J. and K. Matsuura (2001). Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950 - 2014), http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

Insurance Act was passed, expanding the insurance program. In 1994, Congress passed the Crop Insurance Reform Act to subsidize the insurance products at a higher rate to increase participation rates among farmers. This Act nearly doubled participation rates of farmers by the late 1990s. Furthermore, to further encourage participation in the insurance programs, Congress passed the Agricultural Risk Protection Act (ARPA) in 2000 which increased subsidies for coverage levels above fifty percent. Despite all these changes, the formula to determine insurance prices was mostly formulaic and consistent throughout this period (Deryugina and Kirwan 2015). The significant changes came from the differences in premium subsidies over time. The RMA designs the formulas for the insurance rates. Private providers then market these insurance contracts to farmers, as well as insure them. However, these private providers are reinsured by the government.

The Risk Management Agency sets insurance prices using formulas based on past yields by crop, region, county, and individual farmer (for a review, see Coble et al. 2010). The government subsidizes agricultural insurance. While the premium subsidy rates are constant across states, they vary across coverage levels and have been adjusted periodically over time (Deryugina and Kirwan 2015). The rates of yield insurance form the basis for insurance plans that insure for revenue. Other insurance plans rely on different rate-making methodologies, all of which are nevertheless as formulaic as those for yield insurance plans, although not all plans are available for all years.[7] The RMA used the 65 percent coverage level pricing as the benchmark for pricing other coverage levels and insurance products. We use the price on the 65 percent coverage level for yield insurance in our analysis. We document the prevalence of this yield insurance at the 65 percent level in the summary statistics section.

7. See Babcock (2012) for an in-depth overview of the U.S. crop insurance market.

Data Sources

The USDA's Risk Management Agency (RMA) collects data on the insurance decisions of farmers and makes this information publicly available.[8] The insurance data from the USDA Risk Management Agency includes information at the crop-county level on acres insured by coverage level. Furthermore, the data includes the total unsubsidized payment by coverage level and subsidies received by farmers. To calculate the net cost paid by farmers, we subtract the subsidy received from the total payments. Then we divide the total net cost for farmers by the total acres insured to get the insurance price per acre. Thus, we can calculate the price of insurance at each coverage level. We chose the year 2002 for our primary specification as both the take-up rate of insurance as well as the fraction of farmers choosing the yield insurance was high. Though we analyze the years 1997 and 2007 as well.

Subsidy Premiums and Overall Participation Rates

One of the main changes from 1990 to 2007 were the changes in premium subsidies by the government. In 1994, the subsidy percentage was 55, 46, 55, and 24 percent for the coverage levels of 50, 55, 65, and 75 percent. In 1998, coverage levels for 80 and 85 percent were added and subsidized by 17 and 13 percent respectively. When ARPA was passed in 2000, the subsidy level for coverage levels increased for all coverage levels. Figure 2.3 shows the evolution of premium subsidies over time. For example, the premium subsidy increased to 67 percent for a 50 percent coverage level, to 59 percent for the 65 percent coverage level and 48 percent for the 80 percent coverage level. As Deruygina and Kirwan (2015) demonstrate, these increased premium levels increased farmer participation up to 80 percent of the total insurable acreage.

8. http://www.rma.usda.gov/data/sob/scc/index.html.

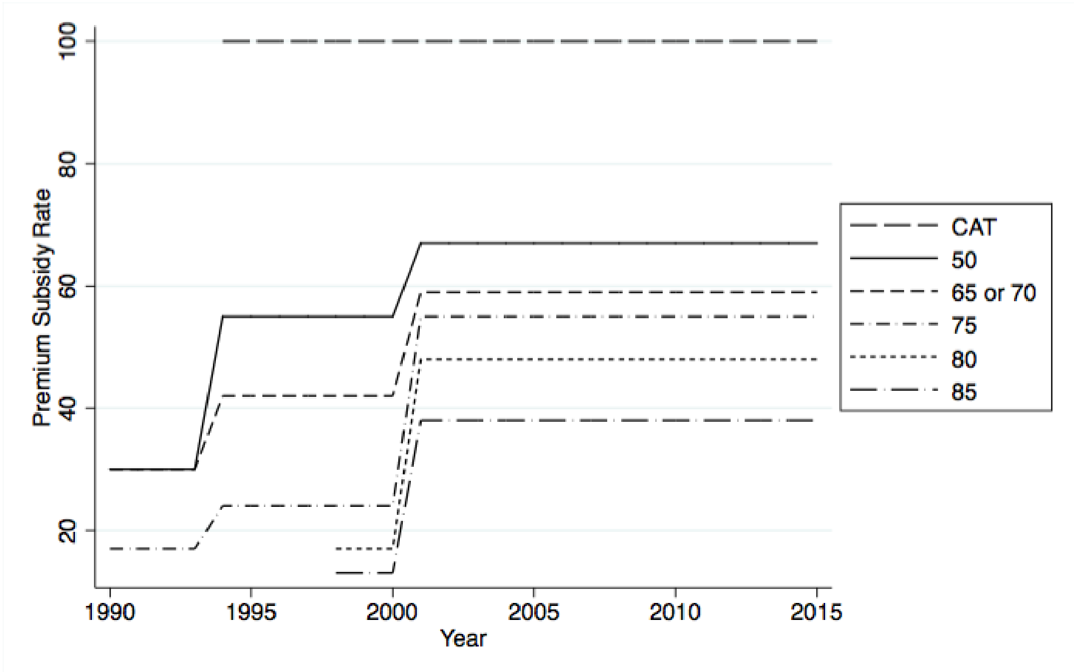

Figure 2.3: Crop Insurance Premium Subsidy Rates from 1990-2011

Note: The national subsidy rate for insurance plans, both yield and revenue, for each coverage level is represented by a line. This subsidy rate assumes that the insurance policy does not combine multiple crops. The data are drawn from the USDA Risk Management Agency Summary of Business files.

Base Rates Calculation and Source of Losses

Premiums are calculated based on the losses of the last 30 years. Zulauf (2016) reports the sources of loss for corn, soybeans, and wheat from 1995 to 2013. For corn, 50 percent of the losses came from drought, 22 percent from excess moisture, 1 percent from freeze and frost, 4 percent from hail and 22 percent from other sources. For soybeans, 42 percent of the losses came from drought, 29 percent from excess moisture, 2 percent from freeze and frost, 6 percent from hail and 21 percent from other sources. Wheat has similar loss percentages as soybeans, although the percentage loss from frost and hail is higher at 9 and 10 percent respectively with lower losses from other sources.

So while counties with similar temperatures will experience similar losses, on average, their insurance costs will be different as other events impact the yields of crops. Because of idiosyncratic losses in the past, based on insects and hail for example, certain counties will have experienced higher losses and thus have to pay a higher premium. Our identification assumption requires that these losses were idiosyncratic and not systematically correlated with unobservables. Given this assumption, counties who are similar will face different insurance costs for crops and therefore make different choices. In other words, we identify the cost coefficient from losses in the past that are not driven by weather or correlated with soil. Thus, we exploit differences among similar farmers who face different insurance costs for crops, after controlling for a rich set of covariates. Furthermore, there are variations in the insurance cost based on the premiums of neighboring countries and the state as a whole (Coble et al. 2010), which induces more variation among counties.

To further explore the mechanisms behind crop insurance, we now discuss the yield insurance in more detail based on a simple analytical set-up by Deryugina and Kirwan (2015). Yield insurance provides the farmer with insurance against yield losses, multiplied by the projected price at the time the contract was signed. Denote the price guarantee by $\bar{P}$, the yield guarantee by $\bar{Y}$, and the actual yield by Y. The insurance is triggered when the yields are below the coverage level. Therefore, the payment to a farmer can be written as:

$$Payment = \bar{P} * \bar{Y} * \frac{max\left(0, \bar{Y} - Y\right)}{\bar{Y}}. \tag{2.4}$$

Furthermore, the RMA uses the average actual yield of the farmer over the past 4 to 10 years as the benchmark for the yield guarantee. This guaranteed yield $\bar{Y}$ will then calculated based on the coverage level, which can be expressed as

$$\bar{Y} = Y^e * cov_{level}. \tag{2.5}$$

Suppose a farmer has a coverage level if 65 percent. This coverage level activates when yields are below 65 percent of their expected yield. Revenue insurance has the same principle but fixes the expected revenue. The baseline insurance now covers the expected yield times the expected price. Anytime the yield times the price drops below the 65 percent revenue, the insurance activates and pays the indemnities to restore the farmer to the 65 percent level.

Coverage Level	Rate Relativity
85%	1.6
80%	1.22
75%	1.00
70%	0.79
65%	0.65
60%	0.51
55%	0.47

Table 2.1: Fixed Coverage Relativities in 1998
Note: This table is based on numbers reported in Coble et al. (2010).

Furthermore, the farmer also gets the benefit of the new prices at harvest time if the harvest price is higher than the projected price at the time the deal is signed. Farmers can opt for a Harvest Price Exclusion (HPE), which excludes this upside of the price but costs less. The RMA determines the cost of revenue insurance based on expected price volatility, where the volatility is calculated from the futures market for the crop. In addition, the RMA uses the historical correlation between yields and prices and a yield distribution curve to predict the average revenues for a farmer and his expected premium payment.

The rates among coverage levels are all based on the 65 percent coverage level. Using projected volatilities, the RMA calculates coverage differentials for each coverage level. The coverage differential translates the base rate of 65 percent into the rates for different coverage levels. Table 2.1 shows the conversion factors as they were set in 1998. Starting in 2002, the RMA started to introduce more flexible rate conversions based on county and farmer characteristics.

2.3.4 Summary Statistics

In our first exercise, we restrict our analysis to the subset of counties for which we have the following variables: Counties who had positive acres harvested for corn and soybeans as well as insurance data for both crops. This selection excludes counties where either corn or soybeans is grown, but not both, or where one of the two insurance prices is missing. In our second exercise, we include a broader sample of both counties and crops. To compare more than two crops, we choose the crops that were planted in more than 50 counties.[9] These crops include barley, corn, cotton, flaxseed, oats, potatoes, sorghum, soybeans, rice, sugar beets, sunflower, and wheat.

For the sample of our first exercise, table 2.2 displays the summary statistics for the crop production of corn and soybeans, farm income, and cropland in this sample relative to 48 contiguous states in the US. Corn and soybeans are grown predominantly in the midwest as Figure 2.4 demonstrates. Table 2.2 shows that over 94 percent of total production and acres are represented in our sample for both corn and soybeans. In other words, we have nearly the full production of corn and soybeans in our sample. While 932 counties that grow corn are excluded, these counties represent less than five percent of overall corn production. This observation also holds for the excluded 416 counties who grow soybean. Among these counties that are excluded, some counties only have one crop that is grown. Other counties do not have insurance data because the availability of crop insurance is not automatic as farmers have to apply to the RMA to have crop insurance introduced for a particular crop (Coble et al. 2010). In addition, the net cash farm income in our sample is 51 percent. Table 2.3 presents futher summary statistics for our sample.

9. When we included crops who were grown in less than 50 counties, we experienced convergence issues.

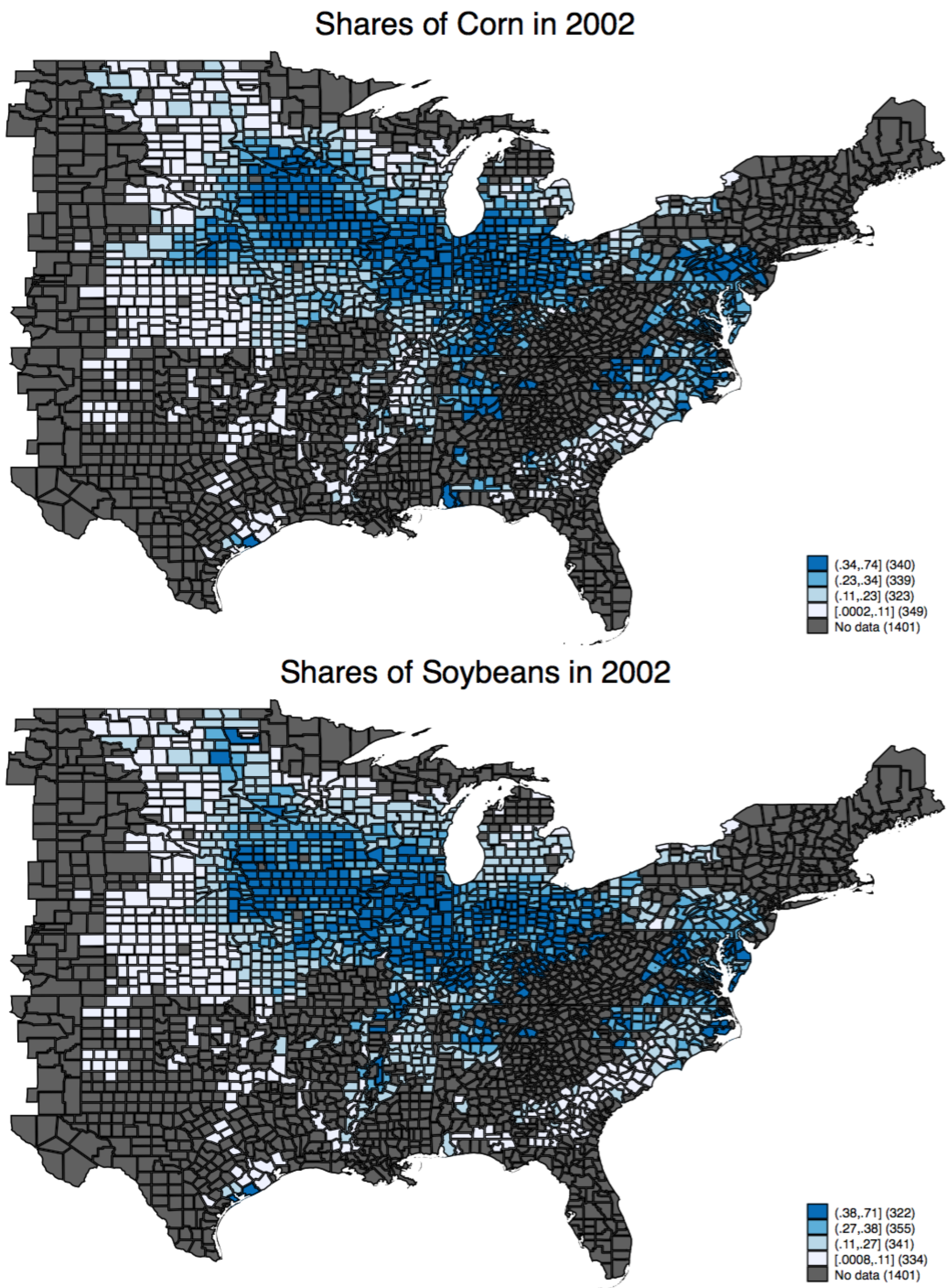

Figure 2.4: Share of Corn and Soybeans in 2002 of All Harvested Acres

Note: This map shows the share of corn and soybeans relative to all harvested acres in 2002 in the sample defined in table 2.3.

Table 2.2: Total Crop Production in Sample vs. Lower 48 Contiguous US States

Crop Variable	Sample (1)	All Lower 48 (2)	Proportion (3)
Corn			
Production (billions of bushels)	8.1	8.6	94%
Acres harvested (millions)	63.7	68.2	94%
Counties with nonzero production	1,352	2,284	59%
Soybeans			
Production (billions of bushels)	2.6	2.7	95%
Acres harvested (millions)	68.1	72.3	94%
Counties with nonzero production	1,352	1,768	76%
Farm income			
Net cash farm income (billions of nominal USD)	20.7	40.3	51%
Counties with nonzero farm income	1,352	3,047	44%
Cropland			
Harvested cropland (millions of acres)	210.3	301.1	70%
All cropland (millions of acres)	264.1	434.1	61%
All cropland + pastureland (millions of acres)	326.8	789.7	41%

Note: The sample is defined as the 1,352 counties that have both corn and soybean acres harvested in the Census of Agriculture, and have insurance cost data for yield insurance at the 65 percent coverage level .

Table 2.3: Summary Statistics for Crops, Climate, and Soil Variables

	Mean	(sd)	Min	Max
Climate Variables				
Growing degree days	3587.29	(431.45)	2572.29	4728.40
Killing degree days	55.44	(43.51)	0.39	239.66
Precipitation (in cm)	550.15	(141.60)	175.55	987.91
Insurance Variables				
Insurance cost corn	4.80	(1.86)	0.57	14.01
Insurance cost soybeans	3.74	(1.71)	1.22	17.12
Soil Variables				
Salinity	-0.01	(0.03)	-0.02	0.43
Flood-prone	-0.03	(0.17)	-0.18	0.77
Wetlands	-0.00	(0.09)	-0.06	0.56
K-Factor	0.02	(0.07)	-0.19	0.18
Slope ength	0.13	(1.23)	-1.74	11.58
Sand	-0.01	(0.26)	-0.08	0.92
Clay	0.01	(0.36)	-0.14	0.86
Moisture capacity	128.10	(286.60)	-256.32	1707.24
Permeability	981.73	(3677.15)	-3036.85	24734.35
Share irrigated	0.07	(0.16)	0.00	0.91
Outcome Variables				
Acres soybeans harvested (th.)	50.61	(53.33)	0.10	524.20
Acres corn harvested (th.)	47.32	(51.89)	0.10	327.00
Acres cropland harvested (th.)	156.38	(119.22)	4.80	1025.10
Acres cropland (th.)	196.27	(140.68)	9.70	1073.00
Acres cropland & pastureland (th.)	242.57	(190.94)	9.80	1501.60
Total acres of land in county (th.)	422.25	(213.40)	84.70	1648.80
Observations	1352			

Note: These are summary statistics for the 1,352 counties that have both corn and soybean acres harvested in the Census of Agriculture, and have insurance cost data for yield insurance at the 65 percent coverage level .

Table 2.4: Climate Means by Year

	2002	2050	2099
Growing Degree Days	3590	4100	4579
Killing Degree Days	56	230	507
Observations	1352	1352	1352

Note: The climate data for 2002 come from the BEST model. The climate projections for 2050 and 2099 come from the RCP 8.5 from ACCESS.

Table 2.4 displays the climate means by year in this sample. The climate data for 2002 come from the BEST model. The climate projections for 2050 and 2099 come from the RCP 8.5 ACCESS model. In our sample, the growing degree days increase by about 400 by 2050 and another 450 by 2099. The killing degree days increase by 160 by 2050 and another 270 by 2099. In addition, the RCP 8.5 is an "aggressive" climate scenario as it predicts the highest increases in temperature among the RCP climate scenarios. Therefore, these predicted increases in degree days could be interpreted as possible upper bounds on damages and gains from adaptation. Therefore, we also use the RCP 4.5 scenario.

Figure 2.5 shows the spatial variation in growing degree days. The southern parts of the country are characterized by more growing degree days, which arises from higher average temperatures. Figure 2.6 shows a similar pattern killing degree days.

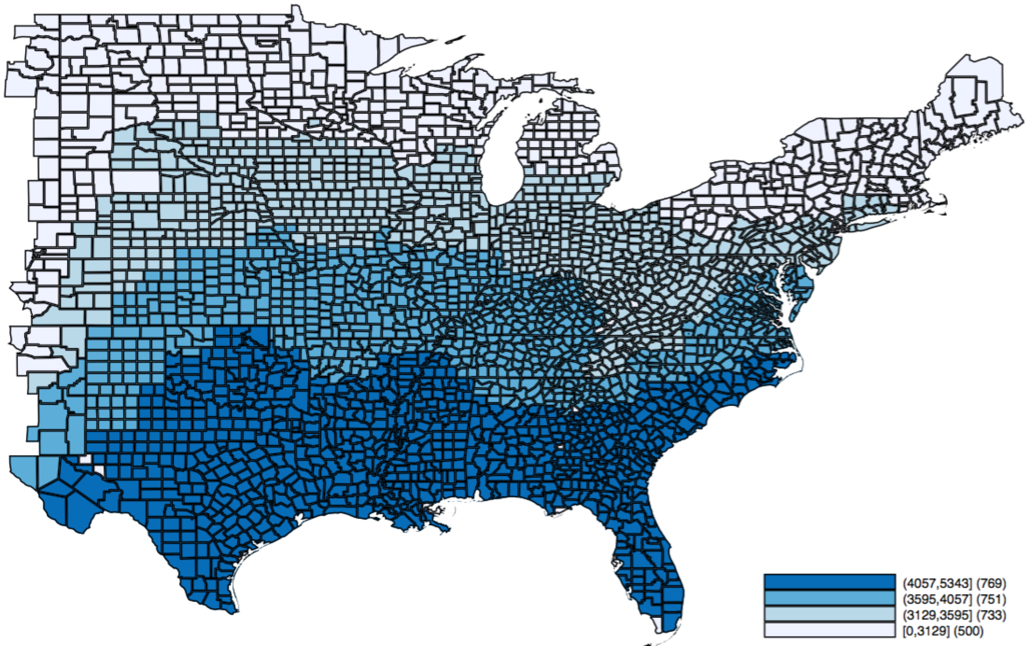

Figure 2.5: Average Growing Degree Days 1971-2001

Note: This map shows the average number of growing degree days from 1971 to 2001 east of the 100th meridian.

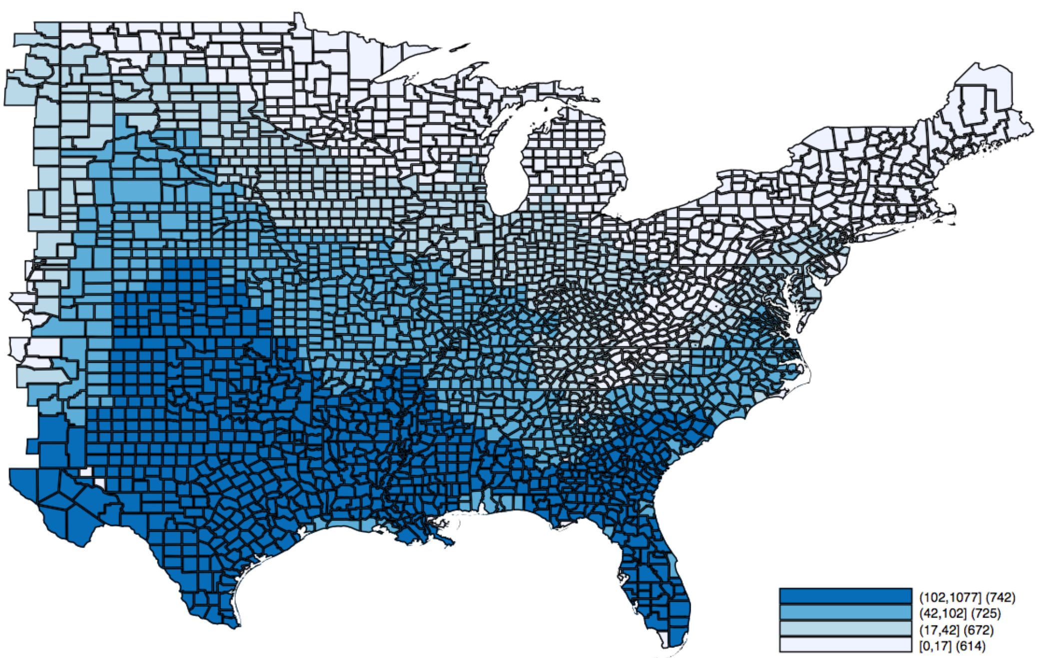

Figure 2.6: Average Killing Degree Days 1971-2001

Note: This map shows the average number of killing degree days from 1971 to 2001 east of the 100th meridian.

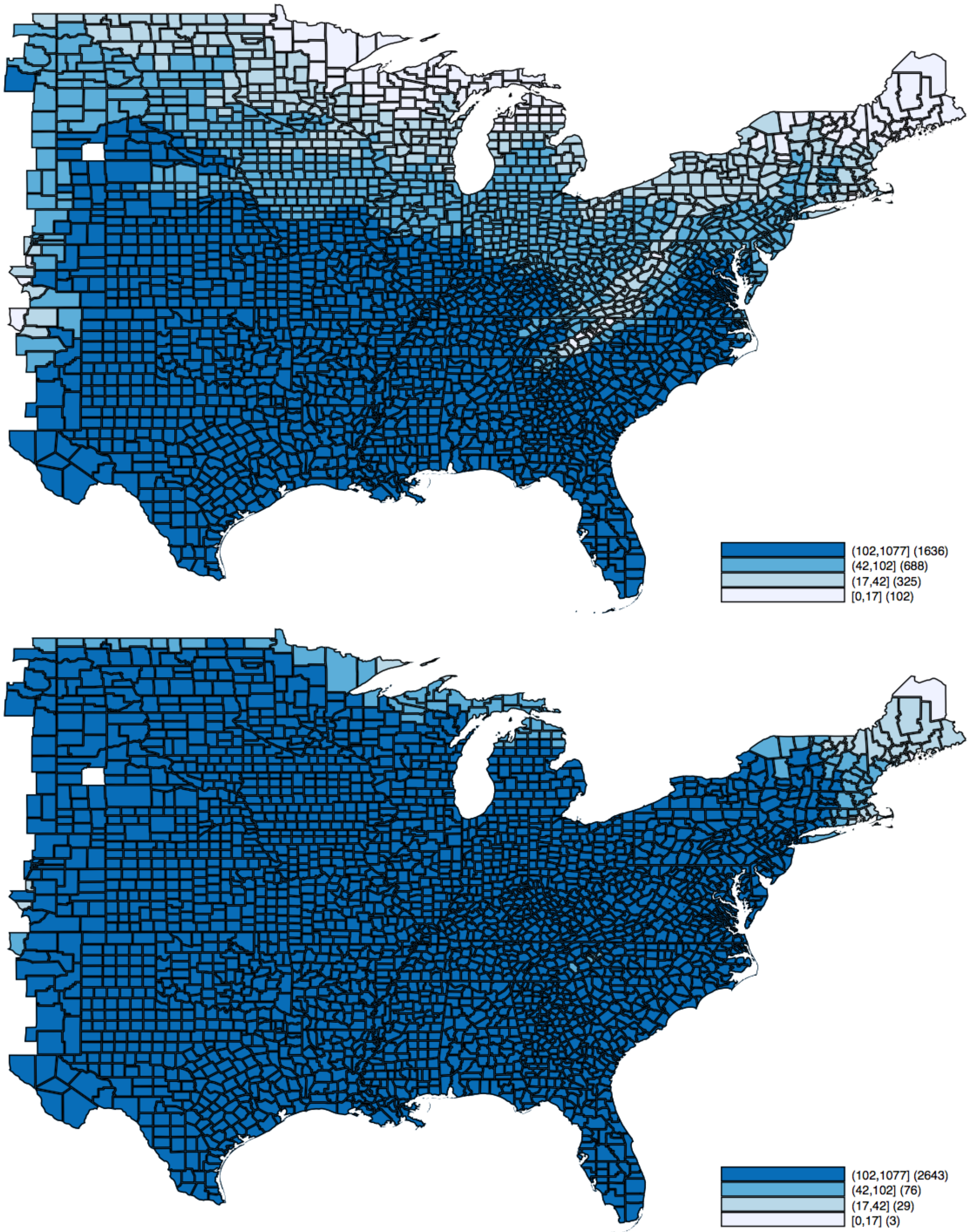

Figure 2.7: Predicted Killing Degree Days in 2030 and 2060
Note: This map shows the predicted number of killing degree days for 2030 and 2060 east of the 100th meridian according to the ACCESS model for the RCP 8.5 scenario.

Table 2.5 presents summary statistics for crop insurance coverage in our sample, in millions of acres. Column 1 contains the acres covered by yield insurance for corn and soybeans. Column 2 contains the acres covered for all insurance types for these two crops. Column 3 calculates the proportion of acres harvested for any given insurance type relative to the total acres harvested. Furthermore, we break down these statistics by coverage levels below, equal to, or higher than 65 percent insurance coverage. Insurance coverage levels range from 50 percent to 90 percent at 5 percent intervals. In our analysis, we will use the yield insurance costs at the 65 percent coverage level.

Over 77 percent of soybeans harvested is insured by some form of insurance in 2002 and up to 84 percent for corn harvested in our sample. For the 65 percent coverage level, soybeans and corn comprise up to 13 and 16 percent of the total acreage of these crops. In our analysis, we restrict our focus to yield insurance at the 65 percent level to keep the insurance costs comparable across counties. Among the farmers who insured at the 65 percent coverage level, 42.8 percent of farmers who grew corn choose yield insurance and up to 71.4 percent for farmers who grew soybeans.[10]

Figure 2.8 displays the spatial variation in the average insurance costs for corn in 2002 for yield insurance at the 65 percent coverage level. The Midwest is characterized by lower insurance prices relative to the other counties. The counties that are situated more south or east have higher insurance prices because losses were higher in the past or because their expected yield is lower (Coble et al. 2010). The insurance prices range from a high of $14 per acre to a low of 60 cents per acre, but most range between $4 and $7 per acre. Figure 2.9 maps out the insurance cost variation for soybeans. This figure shows similar spatial patterns as the costs for corn insurance. The cost of soybean insurance ranges from $1.2 to $17 per acre but are concentrated within the $2.5 to $4.6 range.

10. We are currently investigating ways to map the insurance prices at the other coverage levels onto the 65 percent coverage level.

Table 2.5: Crop Insurance Coverage, in Millions of Acres

Crop Variable	Yield Insurance (1)	All Insurance Types (2)	Proportion of Harvested (3)
Corn			
Coverage level $< 65\%$	8.35	9.52	15%
Coverage level $= 65\%$	4.30	10.03	16%
Coverage level $> 65\%$	3.91	34.24	54%
All coverage levels	16.56	53.79	84%
Soybeans			
Coverage level $< 65\%$	11.03	11.52	17%
Coverage level $= 65\%$	6.35	9.15	13%
Coverage level $> 65\%$	14.49	31.69	47%
All coverage levels	31.87	52.37	77%

Note: The "Proportion of Harvested" column reports the proportion of total acres harvested for the given crop that is covered under any insurance type. 64 million acres were harvested for corn and 68 million acres were harvested for soybeans. For the representative insurance costs, our sample uses yield insurance at the 65% coverage level. Insurance coverage levels range from 50% to 90% at 5% intervals. Acres harvested data are from the USDA. The insurance data are from the Risk Management Agency. All acreage numbers are in millions of acres.

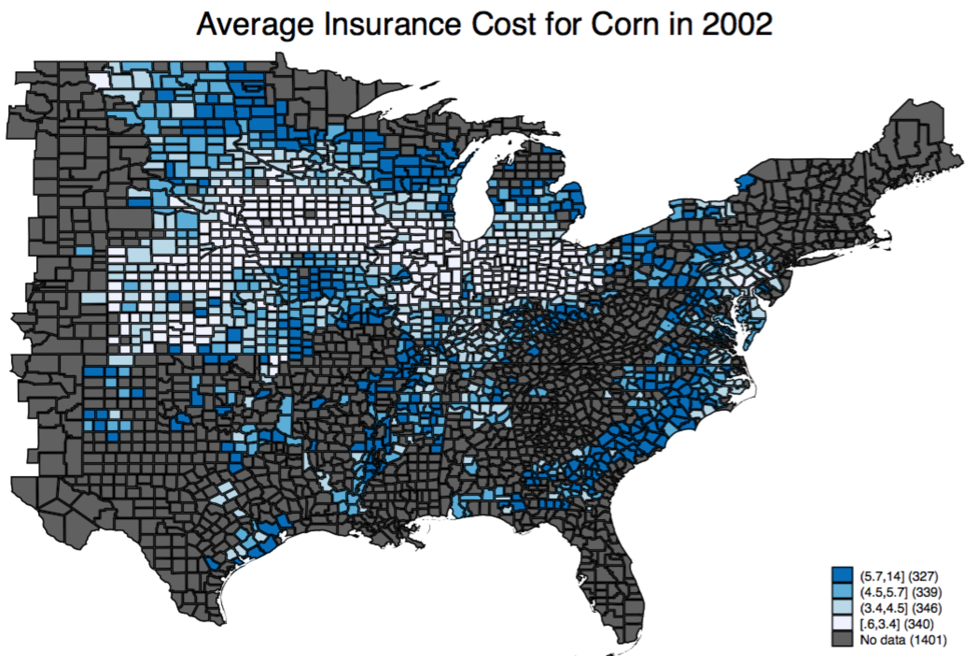

Figure 2.8: Average Insurance Cost per Acre for Corn in 2002
Note: This map shows the average insurance cost per acre for corn in 2002 in our sample of 1,352 counties.

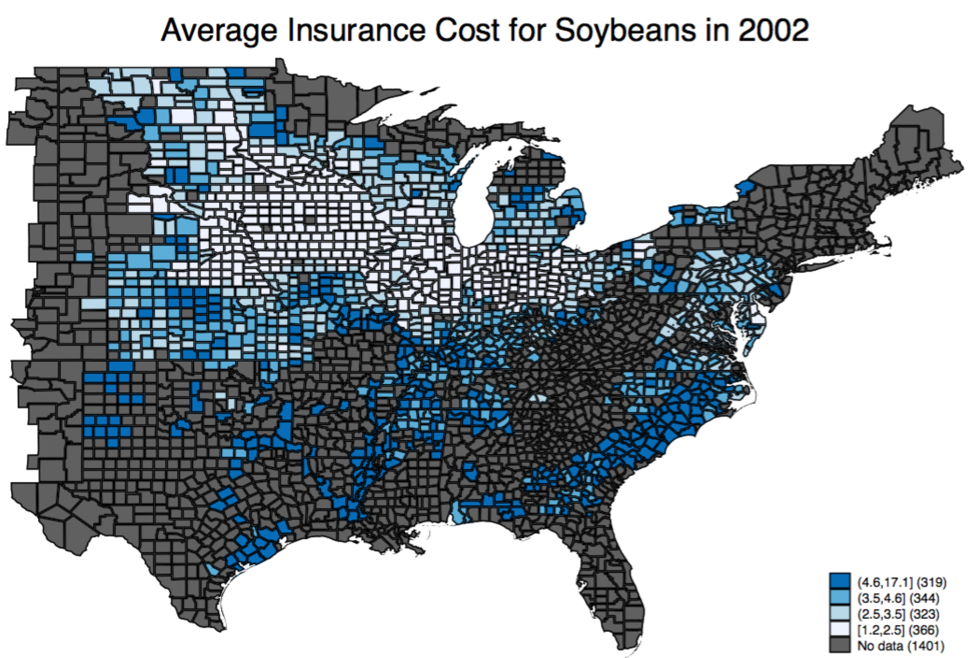

Figure 2.9: Average Insurance Cost per Acre for Soybeans in 2002
Note: This map shows the average insurance cost per acre for soybeans in 2002 in the sample defined in table 2.3.

2.4 Model and Econometric Strategy

2.4.1 Model

In this section, we set up a profit-maximizing model of farmers, the empirical specification, and gains from adaptation. To start, suppose a farmer i operates in county c chooses crop j from the set J, which includes an outside good. Denote the soil variables by $\mathbf{X}_c$, climate variables by $\mathbf{W}_c$, and a cost variable c_{jc}. The farmer maximizes profits:

$$max_{j=1,..,J}\, \Pi_{ijc} \left(\beta_j \mathbf{X}_c + \boldsymbol{\theta}_j \bar{\mathbf{W}}_c + \alpha c_{jc} \right) + \epsilon_{ijc}. \tag{2.6}$$

Whereby j can be any crop. For our first exercise, $j \in$ {corn, soybeans, outside good}. In this set-up, the parameter θ_j accounts for the impact of climate variables on both revenues and costs for crop j, relative to the impact on the outside good. Note that our counterfactual projections assume constant relative prices.

The discrete choice framework can be modeled in several ways. We employ a combination of alternative-invariant regressors, which are temperature and soil variables, and an alternative-varying variable, which is the cost variable c_{jc}, represented by the insurance variable. Another approach is used by Anderson et al. (2012) who construct plant-specific variables and interact these with temperature to obtain only alternative-varying variables. Only having alternative-varying variables is the typical approach in many industrial organization models (see Berry et al. 1995 and Nevo 2001). Equation (2.6) assumes a profit maximization for a single time period t. Dynamic factors, such as crop rotations, are therefore omitted. However, for the Midwest, crop rotations among corn and soybeans do not cause substantial shifts in the equilibrium shares (Hendricks et al. 2014, 1477).

For the cost variable, we use the insurance costs that farmers face. Because of idiosyncratic losses in the past, certain counties will have experienced higher losses and thus have to pay a higher premium.[11] Therefore, we exploit differences among similar farmers who face different insurance costs for crops, after controlling for a rich set of covariates. Furthermore, there are variations in the insurance cost based on the premiums of neighboring countries and the state as a whole (Coble et al. 2010), which induces more variation among counties. If the error terms are distributed according to a i.i.d type 1 extreme value distribution over a crop j and a county c, the probability or share of crop j in county c becomes

$$s_{jc} = \frac{exp\left(\beta_{\mathbf{j}}\mathbf{X}_c + \theta_j\bar{\mathbf{W}}_c + \alpha I_{jc}\right)}{\sum_j exp\left(\beta_{\mathbf{j}}\mathbf{X}_c + \theta_j\bar{\mathbf{W}}_c + \alpha I_{jc}\right)},\ j \in \{1, ..., k\} \tag{2.7}$$

with $s_{0j} = \frac{1}{1+\sum_j exp(V_{ij})}$ (Cameron and Trivedi 2010). In this set-up, the outside good's profit gets normalized to zero.

In this exercise, we face several challenges. A first challenge is that many crops are not currently grown in most counties. For example, cotton might move upwards spatially as temperatures increase, but cotton is only grown in a select set of counties in 2002. As a result, cotton has a zero market share in those counties. The traditional logit model cannot incorporate zero shares of a crop or the outside crop due to logarithm transformation of the ratio of the market shares.[12] There are several ways to deal with this challenge. A first approach is to look at crops that are grown widely and thus have positive market shares. We use this approach as our first empirical specification, whereby we selected corn and soybeans. We then pool the remaining crops with other land uses as the outside good. As such, we do not have a zero share problem and can estimate the equations. A second approach is to use a multivariate fractional regression estimation of econometric share models (Papke and Woolridge 1996, 2008; Mullahay (2010)). A third approach is proposed by Hortasu and Joonhwi (2015) who propose a two-step approach to dealing with zero market shares. Their insight is that the zero market shares are not random but arise based on characteristics. We leverage this approach to include multiple crops, some of which are not grown in certain

11. Examples are the losses from insects or hail.

12. Furthermore, Gandhi et al. (2017) demonstrate that results can be sensitive to very small shares.

counties.

Besides the challenge of zero market shares, there is also the challenge of limited insurance cost data. Insurance cost data is not automatically provided in a county as farmers in a county have to apply to have a specific insurance product for a crop introduced. Furthermore, we need to make assumptions on the cost of insurance if we want to project predicted market shares for other counties which currently have no insurance costs. In this paper, we hold the insurance costs constant at 2002 levels. While this assumption is not fully satisfactory, it does allow us to predict the evolution of market shares from climate change.[13]

2.4.2 Econometric Specification

Following Berry (1994), we take logs to obtain the following specification for the share of crop j in county c:

$$log\left(\frac{s_{jc}}{s_{0c}}\right) = \mathbf{X}_c^{'}\widetilde{\beta}_{\mathbf{j}} + \widetilde{\theta}_j\mathbf{W}_c + \alpha\widetilde{I}_{cj} + \epsilon_{cj}. \tag{2.8}$$

In this log share regression, the parameters $\widetilde{\beta}_j$ and $\widetilde{\theta}_j$ are defined relative to the outside good:

$$\left\{\begin{array}{c} \widetilde{\beta}_j = \beta_j - \beta_0 \\ \widetilde{\theta}_j = \theta_j - \theta_0 \end{array}\right\}.$$

Furthermore, we will use the growing and killing degree days as variables and a quadratic specification in climate:

$$\theta_j\mathbf{W}_c = \theta_{GDD,j}X_{GDD,c} + \theta_{KDD,j}X_{KDD,c}$$

$$+\theta_{Precip,j}X_{Precip,c} + \theta_{Precip,j}X^2_{Precip,c}.$$

To estimate this regression, we employ a system of unrelated regressions on the log of

13. For Canada, we assign insurance prices of the northernmost regions/general US. Footnote: Canada does have some form of crop insurance, but the program works differently, so we choose not to use this data.

relative market shares (Zellner 1962), cluster at the state level, and constrain the price of insurance α to be equal across crops. Given that we are interested in long-run changes, we run our estimation on the cross-section. The current regression thus exploits substantial spatial variation and availability of insurance pricing among corn and soybeans and the outside good from long-run differences in climate. However, the cross-sectional specification is more susceptible to potential omitted variable bias. [14]

Furthermore, we have assumed that the impact of climate is similar across counties, an assumption we will seek to relax in further work. A well-known challenge with the logit framework is that the ratio of shares is independent of other crops (Train 2009). For corn and soybeans, this challenge could be alleviated by pooling corn and soybeans. When dealing with multiple crops, we could create a nested-logit framework with several groups to capture the different substitution patterns among crops or groups. We do investigate the sensitivity of our specification by using various specifications of the outside good involving crops, pastureland, and all other land uses in the county.

Whether a crop is grown at all in a county will depend on the temperature and characteristics of the soil in that county. Therefore, there is a selection bias for crops that are grown. In order to correct for selection, Heckman (1979) proposed a two-step estimator based on a conditional mean restriction.[15] Hortasu and Joonhwi (2015) provide micro foundations for this selection in the context of the discrete choice literature and market shares and derive the following equation:

$$E\left[log\left(\frac{s_{jc}}{s_{0c}}\right) \mid \mathbf{X}_c,\, \mathbf{W}_c,\, \widetilde{I}_{cj},\; s_{jc} \succ 0\right] =$$

14. We control for an extensive set of covariates and weather variables to alleviate this problem. Moreover, we focus on the crop choice of farmers, and not the value of land, which is determined by a much wider array of factors. We are also currently exploring extensions of this paper into a panel setting that would alleviate some of these concerns.

15. Other approaches are to employ a least absolute deviation type estimator under the conditional quantile restriction (Powell 1984, 1986; Blundell and Powell 2007), or symmetric trimming under the symmetry assumption of error terms (Honor et al. 1997).

$$\mathbf{X}_c'\widetilde{\beta}_{\mathbf{j}} + \widetilde{\theta}_j \mathbf{W}_c + \alpha \widetilde{I}_{cj} + \lambda\left(1 - \Psi_\eta\left(-\mathbf{w}_{j,t}'\delta\right)\right) + \epsilon_{cj}.$$

Where $\lambda(\cdot)$ is an unknown smooth function and $\mathbf{w}_{j,t}'$ must have some instrument that shifts the decision of a crop relative to the outside option. While semi-parametric identification would be preferable, in this paper we follow the two-step procedure based on the inverse mills ratio in Heckman (1979). This procedure is provided in Stata by the "Heckman" program. As the instrument, we use the population density in a county, with the identification that the attractiveness for land used for crops or other uses will vary based on the available population and urbanization pressure in the county.

2.4.3 Costs of Climate Change and Gains from Adaptation

We now turn our attention to the impacts of climate change on profits and how much farmers can gain through switching their crops. With the logit framework set up in the previous section, the first observation is that the level of profits is not identified (Train 2009). To obtain a dollar measure, the researcher needs to have a variable that implies a cost to the farmer. In the standard discrete choice setting, this variable would be income, and α would be the marginal utility of income (Train 2009). In our setting, we want to analyze the impacts of insurance cost of farmers. The parameter α allows us to convert the coefficients on the climate variables to the impact on dollars. To summarize, for a crop j, the ratio of the coefficients on a climate variable and the insurance variable gives the WTP for a change in temperature:

$$WTP = \frac{-\frac{\partial \Pi_j}{\partial X_j}}{\frac{\partial \Pi_j}{\partial I_j}} = \frac{-\theta_j}{\alpha}. \tag{2.9}$$

Once we have the WTP, we can calculate what the change of profits will be, relative to the outside good, for a farmer who grows a crop j by multiplying the WTP with the change in climate:

$$\Delta\pi_j = WTP_j * \Delta Climate. \tag{2.10}$$

Given a changing climate, a farmer who holds her choice of crops constant will have damages or benefits relative to the outside good according to

$$\Delta\pi_j = \sum_c \sum_j \left(\frac{\theta_{KDD,j}}{\alpha} * \Delta KDD * share_{j,c} * acres_c \right.$$

$$\left. + \frac{\theta_{GDD,j}}{\alpha} * \Delta GDD * share_{j,c} * acres_c \right).$$

To calculate total damages under full re-optimization, we can replace the shares with predicted shares $\widehat{share}_{t,j,c}$. If farmers are allowed to switch crops, some farmers will still have this change in profits, but this will now only hold for the new predicted shares. The difference between the two scenarios gives the gains from reallocation.

$$\begin{aligned} Adaptation \quad = \quad & \textstyle\sum_c \sum_j \left(\frac{\theta_{KDD,j}}{\alpha} * \Delta KDD * \Delta share_{t,j,c} * acres_c \right. \\ & \left. + \frac{\theta_{GDD,j}}{\alpha} * \Delta GDD * \Delta share_{t,j,c} * acres_c \right). \end{aligned} \tag{2.11}$$

2.5 Results

2.5.1 Regression Results

Using the econometric framework of the previous section, we can now analyze two different crop choice sets. In our first crop choice set, we focus on corn and soybeans relative to other crops. In our second crop choice set, we have multiple crops relative to the outside option. The results of our first specification with corn, soybeans, and the outside good are shown in Table 2.6. We have controlled for soil variables, irrigation, precipitation, and precipitation squared in all regressions. The standard errors are calculated using feasible GLS according to Zellner's unrelated regression (1962), which accounts for the correlation of the error terms across equations. This method estimates the variance-covariance matrix in the first stage

Table 2.6: Regression Results Explaining Crop Choices

	(1)	(2)	(3)	(4)
Insurance Cost	-0.31***	-0.31***	-0.28***	-0.29***
	(0.017)	(0.016)	(0.016)	(0.016)
Corn				
Growing Degree Days (GDD)	0.0043***	0.0039***	0.0040***	0.0026***
	(0.00027)	(0.00024)	(0.00024)	(0.00024)
Killing Degree Days (KDD)	-0.052***	-0.048***	-0.050***	-0.037***
	(0.0024)	(0.0022)	(0.0022)	(0.0022)
Soybeans				
Growing Degree Days (GDD)	0.0048***	0.0044***	0.0045***	0.0031***
	(0.00024)	(0.00022)	(0.00023)	(0.00023)
Killing Degree Days (KDD)	-0.053***	-0.049***	-0.052***	-0.038***
	(0.0022)	(0.0020)	(0.0021)	(0.0021)
Harvested Cropland	Yes	Yes	Yes	Yes
Other Cropland		Yes	Yes	Yes
Pasture Land			Yes	Yes
Other Land				Yes
Share of all Land	37%	43%	57%	100%
Observations	1352	1352	1352	1352
R squared	0.598	0.617	0.621	0.555

Note: All specifications also control for soil variables, irrigation, precipitation, and precipitation squared. The standard errors are calculated using feasible GLS according to Zellner's unrelated regression (1962), which accounts for the correlation of the error terms across equations. This method estimates the variance-covariance matrix in the first stage from the OLS residuals and uses these to run a GLS regression with this variance-covariance.

from the OLS residuals and uses these to run a GLS regression with this variance-covariance matrix.

For sensitivity analysis, we vary the definition of the outside good. Each of these outside goods contains all the land described, minus the acres harvested for corn and soybeans. In column 1, the outside good is all harvested cropland as the outside good, whereas it is inclusive of all cropland in column 2. In column 3, pasture land has been added, whereas column 4 uses the total surface area in a county. We have included the fraction of land that is captured by a specification relative to the total surface area as a row. An increased fraction thus denotes more substitution possibilities.

For all specifications, the coefficients for growing degree days are positive. These coefficients indicate the impact of a unit increase of growing degree days on the logarithm of the ratio of the share of corn or soybeans over the share of the outside good. These positive coefficients indicate that farmers are more likely to grow corn and soybeans as the growing degree days increase. An increase in killing degree days makes farmers less likely to grow corn or soybeans. Furthermore, the coefficients on corn and soybeans are similar. This similarity is not surprising given that the impacts of temperature for corn and soybeans are quite close (Burke and Emerick 2016). Farmers are also less likely to grow corn and soybeans when insurance costs are higher.

Table 2.7 converts the coefficient of table 2.6 into WTP measures for changes in climate for each crop. When we specify cropland and pastureland as the outside good, farmers are willing to pay 1.4 cents to gain a growing degree day and pay 17.9 cents to avoid an increase of a killing degree day on land growing corn. For soybeans, the willingness to pay to gain a growing degree day is 1.6 cents and 18.6 cents to avoid a killing degree day.

Table 2.7: Willingness to Pay Results for Corn and Soybeans

	(3)	(4)
Corn		
WTP for GDD	0.014	0.009
WTP for KDD	-0.179	-0.128
Soybeans		
WTP for GDD	0.016	0.011
WTP for KDD	-0.186	-0.131
Harvested Cropland	Yes	Yes
Other Cropland	Yes	Yes
Pasture Land	Yes	Yes
Other Land		Yes
Share of all Land	57%	100%
Observations	1352	1352

Note: These are willingness to pay results based on table 2.6. All specifications control for soil variables, irrigation, precipitation, and precipitation squared.

One limitation of these results is that the outside good specification is a combination of different crops and other uses of land, which makes the interpretation of the WTP measures less straightforward. Therefore, farmers could switch to multiple other crops, to pasture land, or fallow land. While we can thus shed light on the substitution patterns of corn and soybeans, what farmers are switching towards is still unclear. Therefore, we expand our choice set of crops in our second exercise.

When we include more crops, we gain more detail but face the challenge that some grows are only grown in specific regions. As a result, the share of these crops will be zero in many counties. Using the selection correction laid out in the econometric framework, we can use a two-step procedure to estimate the coefficients. Table 2.8 reports the regression coefficients of this exercise for the census years 1997, 2002, and 2007 as well as for varying outside good specifications. Our results are robust to the choice of census year, even though the premium subsidies for insurance do vary substantially across these years. The signs on the coefficients for corn and soybeans are similar to our previous exercise for growing and killing degree days. Table 2.9 converts these numbers into WTP measures using the same column numbers and outside good specifications as in Table 2.8.

As the coefficients on alternative-varying regressors are relative to the coefficient of the outside good, the less the outside good is impacted by a killing degree day, the higher the cost will be to a farmer who grows a specific crop. Therefore, we would expect the WTP measures to be higher if we take more crops out of the outside good and integrate them as a choice, which is confirmed in Table 2.9. Column 2 can be compared to the estimates in Table 2.7. The WTP for a growing degree days goes up from 1.4 cents to 2.5 cents, and the WTP to avoid a killing degree day increases from 17.9 cents to 32.3 cents. Similarly, the measures for soybeans go up from 1.1 cents to 3.2 cents for growing degree days and from 13.1 to 36.9 cents for killing degree days. These results confirm that the other crops will be more affected than pasture land or woodland.

Table 2.8: Regression Results Explaining Crop Shares

	(1)	(2)	(3)	(4)
Cost per acre	-0.13***	-0.13***	-0.086***	-0.083***
	(0.026)	(0.031)	(0.024)	(0.014)
Growing degree days	0.00052	0.00022	-0.00035	0.00062
	(0.00082)	(0.00086)	(0.00084)	(0.0011)
Killing degree days	-0.013**	-0.012*	-0.0025	-0.012
	(0.0056)	(0.0068)	(0.0048)	(0.0088)
Corn × Growing degree days	0.0016	0.0030*	0.0020	0.0012
	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Soybeans × Growing degree days	0.0023*	0.0040***	0.0031**	0.0018
	(0.0013)	(0.0016)	(0.0016)	(0.0014)
Corngrain × Killing degree days	-0.019**	-0.030***	-0.031***	-0.013
	(0.0089)	(0.011)	(0.0092)	(0.0096)
Soybeans × Killing degree days	-0.022***	-0.036***	-0.031***	-0.017
	(0.0085)	(0.011)	(0.011)	(0.011)
Observations	31281	30901	30819	30705
Cluster	State	State	State	State
Year	2002	2002	1997	2007
Outside Good	All	Pasture	All	All

Note: These results were estimated with the 2-step "heckman" command in stata. The observations represent the total number of crop-county observations. All specifications control for soil variables, irrigation, precipitation, and precipitation squared. For the outside good, "All" denotes all land in county, whereas "Pasture" denotes all cropland and pastureland. For each of these, the outside good is calculated as the total acres minus the acres of the included crops in the sample.

Table 2.9: Willingness to Pay Results Using Multiple Crops

	(1)	(2)	(3)	(4)
Corn				
WTP for GDD	0.016	0.025	0.019	0.022
WTP for KDD	-0.246	-0.323	-0.390	-0.301
Soybeans				
WTP for GDD	0.022	0.032	0.032	0.029
WTP for KDD	-0.269	-0.369	-0.390	-0.349
Year	2002	2002	1997	2007
Harvested Cropland	Yes	Yes	Yes	Yes
Other Cropland	Yes	Yes	Yes	Yes
Pasture Land	Yes	Yes	Yes	Yes
Other Land	Yes		Yes	Yes

Note: These are willingness to pay results based on Table 2.8. All specifications control for soil variables, irrigation, precipitation, and precipitation squared.

2.5.2 Predicted Changes in Shares

With the results of our first exercise, we can now predict how the shares of corn and soybeans, relative to the outside good, will evolve during this century.[16] For this prediction, we use column 3 of table 2.6, which uses total harvested land and cropland as the reference category. Using the RCP projections, we predict the log-share ratios for each year and then convert them back into shares. Figure 2.10 shows this predicted evolution of the share of corn and soybeans for the rest of the century for the ACCESS model under the RCP 8.5 scenario. Both corn and soybeans follow similar trends over time, which arises from their similar regression coefficients. Their shares start at an average of 25 percent in 2010 but then decrease over time. While the increase in growing degree days would lead to an increase of shares, the increase of killing degree days more than offsets that positive effect based on the climate projections from ACCESS. The shares of corn and soybeans sharply decrease over time and drop to 5 percent by mid-century and then further decrease by the end of the century. Figure

16. We are in the process of generating similar predictions for our regression results with multiple crops.

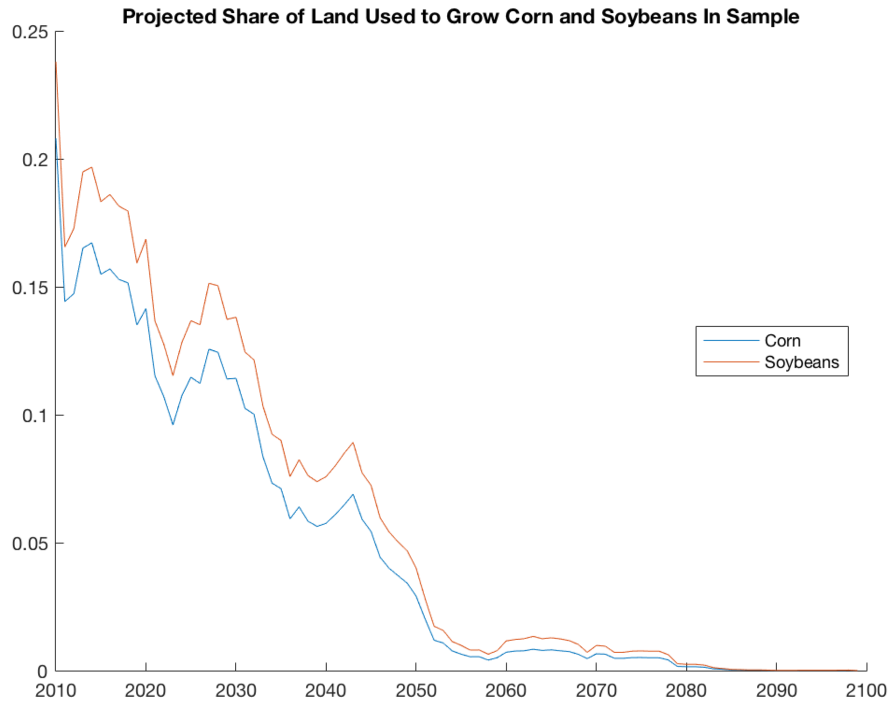

Figure 2.10: Projected Crop Shares of All Harvested and Pasture Land
Note: These predictions are for the sample of 1,352 counties defined in section 2.3 using the regression results of column 3 in table 2.6. The predictions use the RCP 8.5 scenario of the ACCES model.

2.11 graphically captures these predicted shares for the RCP 4.5 scenario. For this scenario, a similar pattern evolves for the predicted shares although the decline in shares is slower due to the slower increase of killing degree days.[17] Remarkably, the share of corn and soybeans does rise again near the end of the century, which can arise from a larger increase of growing degree days relative to killing degree days.

17. We are in the process of expanding our results by creating predictions from other climate models. From our first comparison, it seems that the ACCESS climate model provides more substantial increases in temperatures than the other climate models, so these results would be an upper bound on how fast the shares of corn and soybeans would decrease over time.

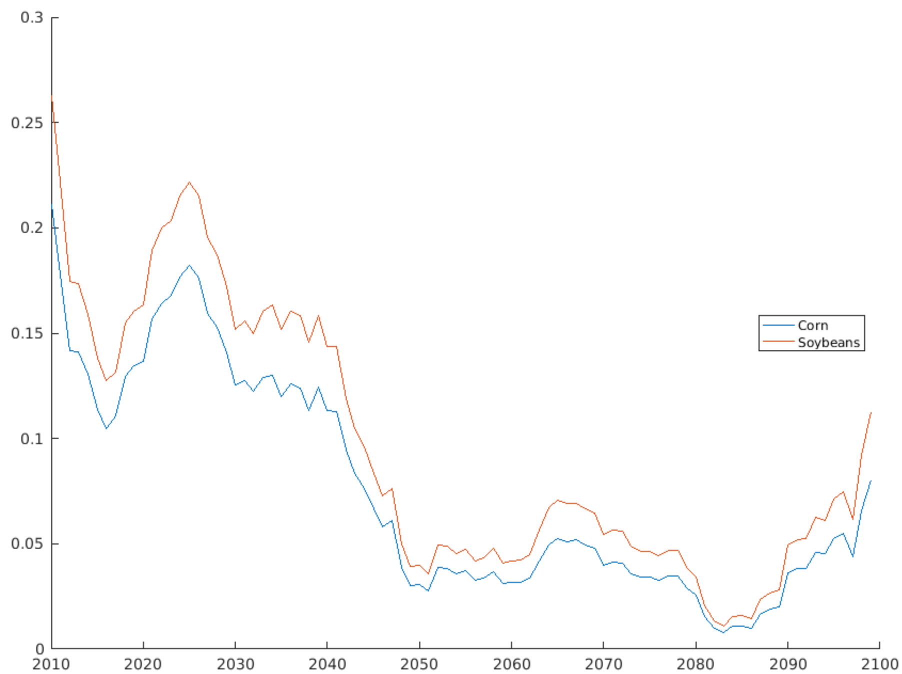

Figure 2.11: Projected Crop Shares of Corn and Soybeans Relative to All Harvested and Pasture Land

Note: These predictions are for the sample of 1,352 counties defined in section 2.3 using the regression results of column 3 in table 2.6. The predictions use the RCP4.5 scenario of the ACCES model.

Figure 2.10 shows the average share in our sample but does not capture the spatial impacts. Figures 2.12 and 2.13 capture these spatial shifts in corn and soybeans from 2010 to 2060. For both corn and soybeans, farmers are decreasing their share. Not surprisingly, farmers keep growing corn and soybeans in the counties that are most suitable for their production, characterized by the initial highest shares of these crops in 2002. As time goes on, the shares decrease until only some of the most northern counties still produce some corn and soybeans. The shares never reach zero as the logit model has an intrinsic feature that predicted shares are always positive. In Figure 2.10, we have set counties in which the share of corn is less than 0.08 percent as missing data to illustrate the substantial changes in shares. Crops are decreasing uniformly across counties. Moreover, they seem to be migrating north towards regions with lower killing degree days. Therefore, our results suggest that Canada might see a large increase of farmers who grow corn or soybeans.

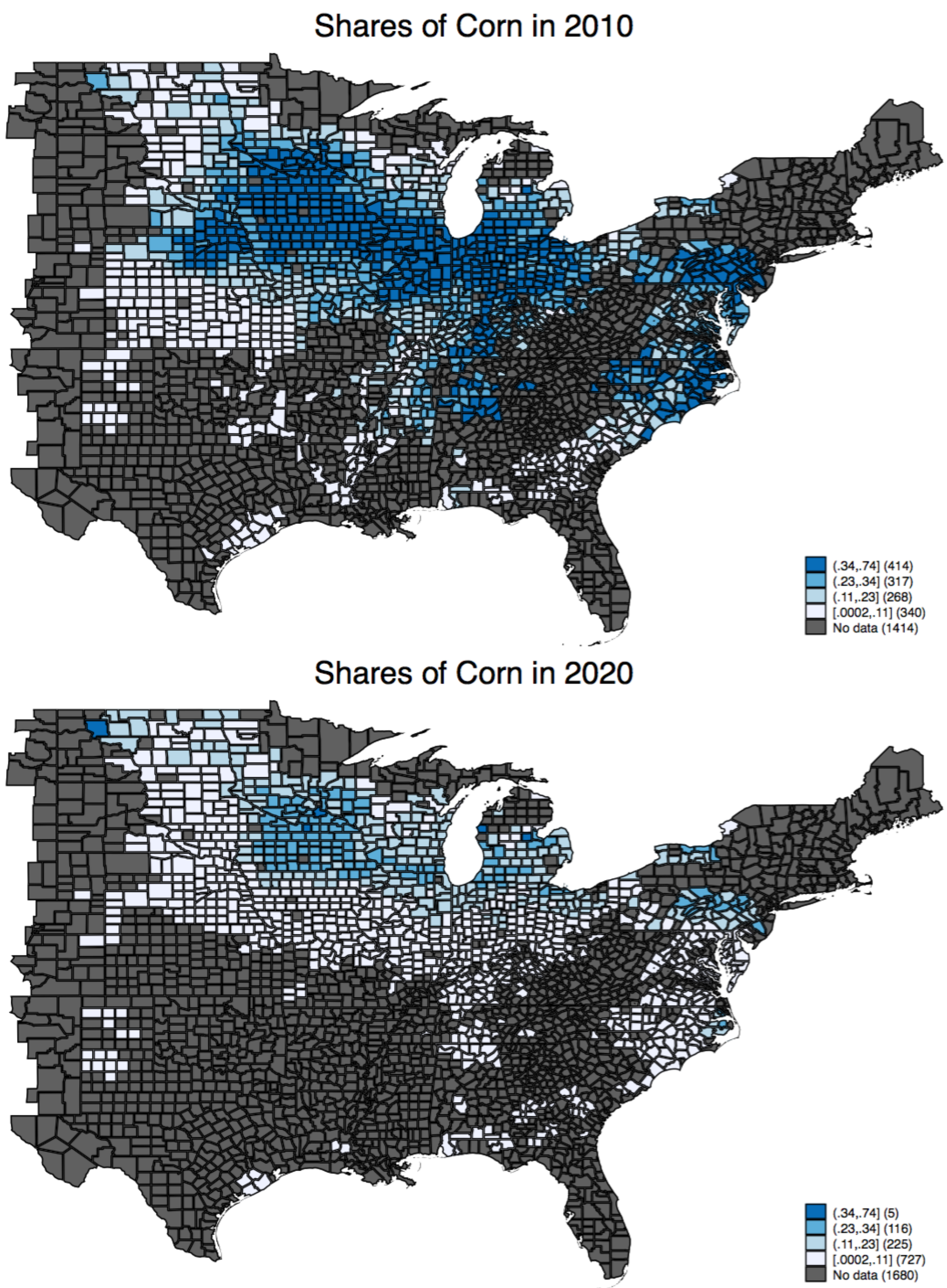

Figure 2.12: Climate Predictions for the Shares of Corn for 2010 and 2020

Note: These predictions are for the sample of 1,352 counties defined in section 2.3. Counties in which the share of corn is less than 0.08 percent are set as missing data to illustrate the changes in shares.

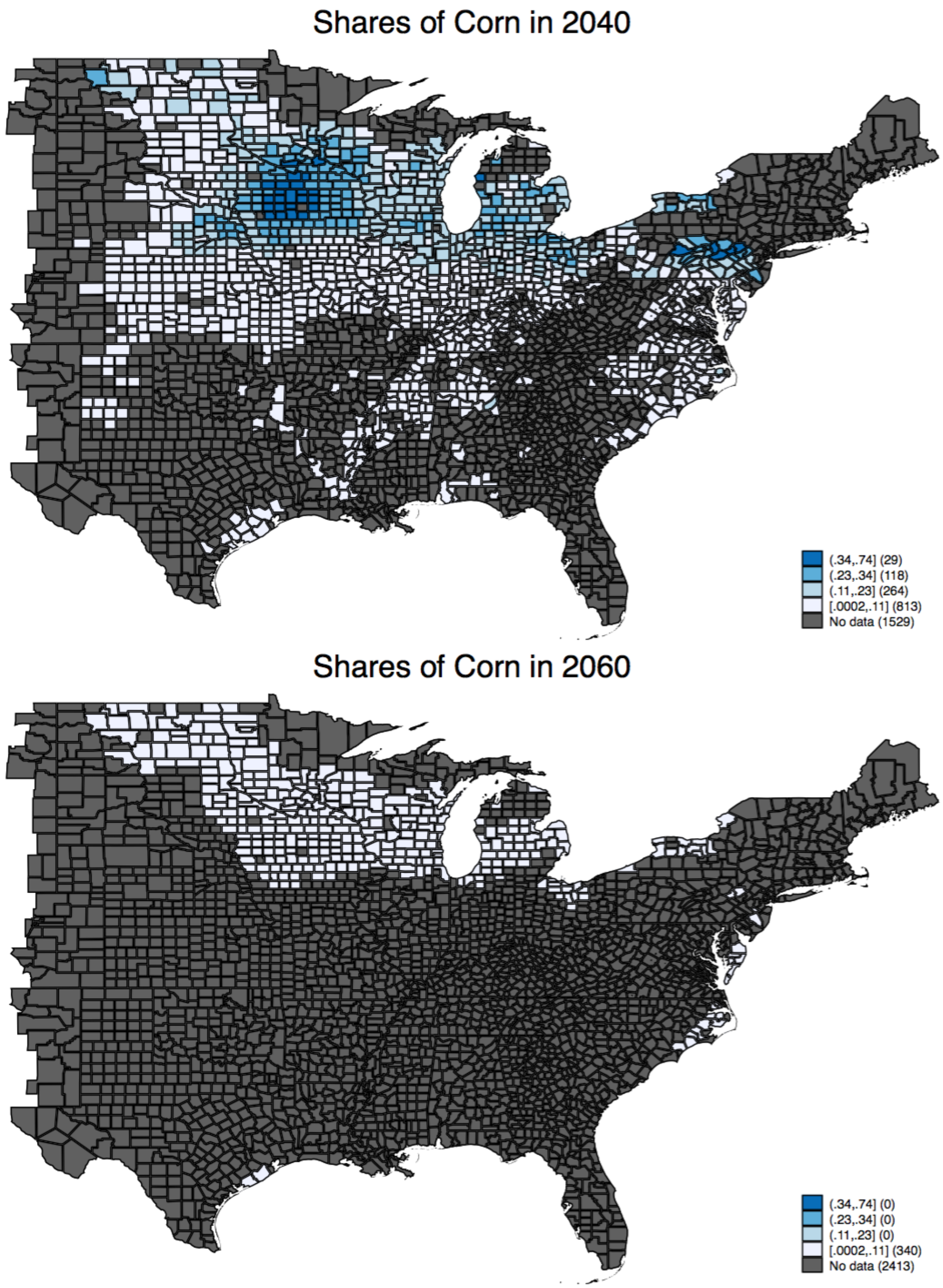

Figure 2.13: Climate Predictions for the Shares of Corn for 2040 and 2060

Note: These predictions are for the sample of 1,352 counties defined in section 2.3. Counties in which the share of corn is less than 0.08 percent are set as missing data to illustrate the changes in shares. The predictions use the RCP 8.5 scenario of the ACCES model.

2.5.3 Gains from Adaptation from Crop Choice

Using equation (2.11), we can calculate the gains to farmers of switching their crops. Figure 2.14 shows the impacts of the scenarios where the farmer cannot switch crops or the scenario where reallocation is allowed. When farmers cannot switch their crops, they experience higher levels of damages over time. While the increase in growing degree days would lead to an increase of profits, the increase of killing degree days more than offsets that positive effect based on the combination of the killing degree day coefficient and increases in killing degree days. When farmers can switch their crops, the damages initially increase but then decrease from 2040 onwards because the shares of corn and soybeans drastically decrease. Therefore, the difference between these lines represents the gain to farmers from switching crops.

In the previous section, we found that the predicted shares of corn and soybeans decrease quite substantially by mid-century when we combine the ACCESS climate projections and the regression. However, even though shares of corn and soybeans are minimal by mid-century, the projected gains from adaptation would still increase according to equation (2.11). However, if the shares are minimal, then there will be no actual gain of adapting anymore. Therefore, Figure 2.15 plots the gains from adaptation until 2060. Given that the levels are not identified in the logit model, these profit impacts relative to the outside good are only full costs if the damages to the outside good are zero. For example, if a piece of land is never used, then the impact of more extreme temperatures on the profitability of that land is zero. In this example, the WTP measure would capture the full profit impacts for a specific crop.

Figure 2.15 shows that climate damages are systematically lower when farmers re-optimize land use than in the fixed crop choice scenario. Climate damages will be around \$8.9 to \$11.8 in 2050 for the RCP 4.5 and 8.5 scenarios when farmers re-optimize land use relative to a scenario where farmers cannot change the crop they grow. Given that the total farmer profit in our sample is around \$21 billion, farmers can thus gain substantial benefits from adaptation through crop switching.

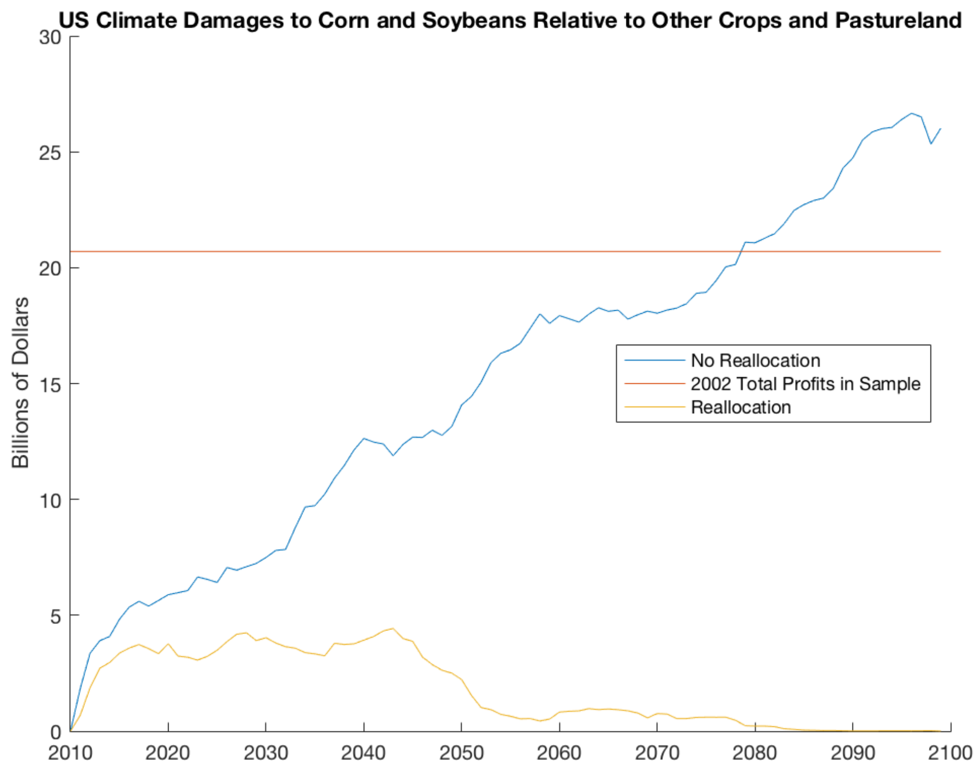

Figure 2.14: Projected Impacts from Climate Changes

Note: These predictions are for the sample of 1,352 counties defined in section 2.3 using the regression results of column 3 in table 2.6. The predictions use the RCP 8.5 scenario of the ACCES model. Harvested land and pasture land are the reference category. See the text for more details.

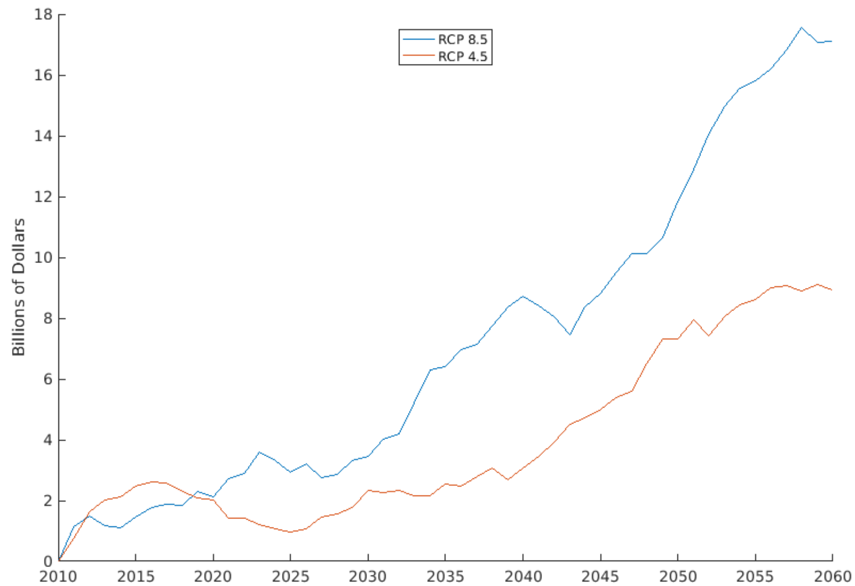

Figure 2.15: Projected Gains from Reallocating Away from Corn and Soybeans
Note: These predictions are for the sample of 1,352 counties defined in section 2.3 using the regression results of column 3 in table 2.6. The predictions use the RCP 4.5 and 8.5 scenarios of the ACCES model. Harvested land and pasture land are the reference category. See the text for more details.

2.6 Conclusion

In this paper, we investigate how much farmers can adapt to climate change through their choice of crops. Using data on insurance costs, combined with a discrete choice framework, we estimate the impacts of predicted climate changes in climate on farmer profits, relative to the outside option. We find that climate change will produce a substantial reduction in the share of land used to grow corn and soybeans in the US over the next century. In addition, farmers who grow corn are willing to pay between 1.4 and 2.5 cents for beneficial temperatures depending on the specification, while they are willing to pay between 17.9 and 32.3 cents to avoid an increase in extreme temperatures above 29 °C. These results are robust across census years and outside options. When we allow farmers to re-optimize their land use, climate damages in 2050 are \$8.9 to \$11.8 billion lower depending on the climate change scenario.

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