THE IMPACTS OF CLIMATE CHANGE AND ENERGY POLICY ON U.S. AGRICULTURE

By

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ABSTRACT

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Agriculture is vulnerable to both natural and human-made changes. In the past few decades, changes in climate and energy policy have transformed U.S. agricultural production. From the perspective of economics, I am interested in the impacts of climate change and energy policy on agriculture, which are intensively investigated in my dissertation essays.

In my first essay, I measure the impacts of climate change and adaptation on U.S. agriculture. Climate impact assessment models that ignore adaptation and technological change may overestimate the damage or underestimate the benefits from climate change. To address this issue, I investigate the impacts of climate change on farmland value accounting for adaptation, such as land-use change and technological change. My joint structural econometric model of farmland value and crop choices captures the complex interactions between crop prices, crop biological and physiological attributes (e.g., stomata density and root depth) that are correlated with crop stress resistance, and soil and climate characteristics. Thus, my model also allows me to measure the economic values of a series of adaptation strategies and quantify the heterogeneous impacts of climate change due to different initial conditions. My research has far-reaching applications for the agricultural industry, university extensions, and government agencies in guiding crop research and development, identifying vulnerable regions, and prioritizing funding allocation in adaptation to climate change.

In my second essay, I determine the land-use change induced by the demand for bioenergy crops. Although deforestation is a concern for biomass promotion, empirical evidence is widely lacking. In this paper, I empirically estimate land-use changes associated with an emerging

biomass market and a newly implemented biomass subsidy. The opening of a large-scale biomass processing plant in Missouri and the subsequent Biomass Crop Assistance Program shift the local demand for bioenergy crops and create heterogeneous supply incentives for farmers near to versus far away from the plant. Using a difference-in-differences approach, I find that the plant opening slightly induces land switching from forest to food crops, while the BCAP subsidy program not only significantly induces bioenergy crop supply, but also discourages deforestation, illustrating the environmental gains from the policy.

Collectively, my dissertation provides guidance to policy makers that hope to promote sustainable agriculture in a rapidly changing environment.

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I thank my parents for educating and raising me to be an independent person. I thank my parents-in-law for taking care of my son. I thank my husband, Daoming, for all the years around me. I thank my son, Adrian, for being so sweet.

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Introduction

Climate variability and the need for cleaner energy have drawn the attention of policy makers to the importance of sustainable development. However, the impacts of climate change and energy policy need to be carefully studied to guide policy decisions. This dissertation develops microeconomic and econometric models to measure the impacts of climate change, assess the costs and benefits of adaptation strategies, and evaluate the effects of energy policies on agriculture, which is a unique industry that is particularly sensitive to climate change and which may play an important role in making our energy system more sustainable.

From the agronomy literature, we learn that abiotic stress is responsible for the majority of crop yield losses in agriculture. Facing the rapidly changing climate, agriculture may be even more fragile than before, especially if farmers cannot swiftly adapt to climate change (Antle 2009). Food security in developing countries under climate change and rising crop prices (caused by energy expansion) is a major concern, therefore, prioritization of adaptation funding allocation is urgent (Lobel 2013). However, the economics literature has not provided sufficient evidence on the impacts of climate change on agriculture and the economic values associated with attainable adaptation strategies. In my first dissertation chapter, I try to fill this gap by estimating a joint structural econometric model of farmland value and land-use choice with an embedded reduced-form crop production function. The model allows me not only to determine the heterogeneous impacts of climate change but also measure the monetary values of a series of adaptation strategies.

Under the call for a cleaner environment and less dependence on foreign oil, the U.S. government has implemented several renewable energy policies. One of the major debates of replacing gasoline with biofuels is that net carbon emissions may ironically increase via indirect land-use change. Unfortunately, empirical evidence on land-use change (both direct and indirect) induced by biofuel policies is widely lacking. In my second dissertation chapter, I conduct a difference-in-differences analysis to show the impacts of a biorefinery and the impacts of the Biomass Crop Assistance Program on land-use changes.

In sum, my dissertation integrates the impacts of climate change, the economic values of adaption strategies, and the empirical evidence of land-use changes induced by existing bioenergy policy. The far-reaching implications of my research can be used by policy makers at various levels, private investors, and university extensions and other institutions who are concerned about the sustainability of agriculture.

Chapter 1 Adaptation to Climate Change in U.S. Agriculture: The Role of Crop Physiological Attributes in Farmland Value Formation

Agriculture—for which temperature and rainfall are direct and major inputs into production—is one of the sectors most vulnerable to climate change. Indeed, cold, drought, and excess water are responsible for 71% of past crop yield losses (Boyer, 1982). The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report predicts more frequent climate extremes in the future, which may make agriculture even more fragile than ever. On the other hand, opportunities for climate adaptation—such as moving planting dates, expanding irrigation, adopting new crops and crop varieties, and switching land-uses—are substantial (Boyer 1982; Schlenker and Roberts 2009; Butler and Huybers 2013; Zilberman, Zhao, and Heiman 2013). Recent generations have witnessed a massive increase in agricultural productivity due to mechanization and technological change. Therefore, climate change impact assessments that ignore adaptation and technological change are likely to overestimate climate damages and underestimate climate benefits (Greenstone, Kopits, & Wolverton, 2013).

To address these issues, I econometrically estimate a joint structural model of crop choices and farmland value using U.S. county-level data for 1978-2007. I trace the differential returns to growing two-dozen field crops across different counties through a series of interactions between crop prices, county soil and climate characteristics, and quantifiable crop physiological attributes (e.g. root depth and stomata density) that correlate with yield response to climate and soil conditions. Thus, my model allows me to study the heterogeneous impacts of climate change on crop yield, land-use choice, and farmland value across counties in a unified framework.

I predict county-level changes in farmland value due to marginal changes in climate. I find that a one centimeter increase in *rainfall deficiency* (more drought) during the growing season leads to changes in county farmland value ranging from -100%[1] to -0.2%, while a one centimeter increase in *rainfall surplus* (more flood) leads to changes in farmland value ranging from -3.1% to +53%. Meanwhile, a one degree Celsius increase in *temperature deficiency* (more cold) leads to changes in county farmland value ranging from -100% to +0.8%, while a one degree Celsius increase in *temperature surplus* (more heat) leads to changes in farmland value ranging from -13.3% to +0.1%. My results imply that a uniform 2.8°C (5°F) increase in temperature and 8% increase in precipitation (which are conventional predictions for a CO_2 doubling scenario) across all U.S. counties would lead to an overall increase in U.S. farmland values of 5%. Moreover, the selective adaptation of crop attributes via the adoption of new crop varieties (i.e., super-soybeans, which have 30% more stomata density—a correlate of drought tolerance), attribute-enhancing chemicals (i.e., spray to increase the stomata density of all crops by 10%), and new crops (i.e., crops have not been cultivated locally) would reinforce the beneficial impacts of climate change by an additional 2.2%, 2.4%, and 13.8%.

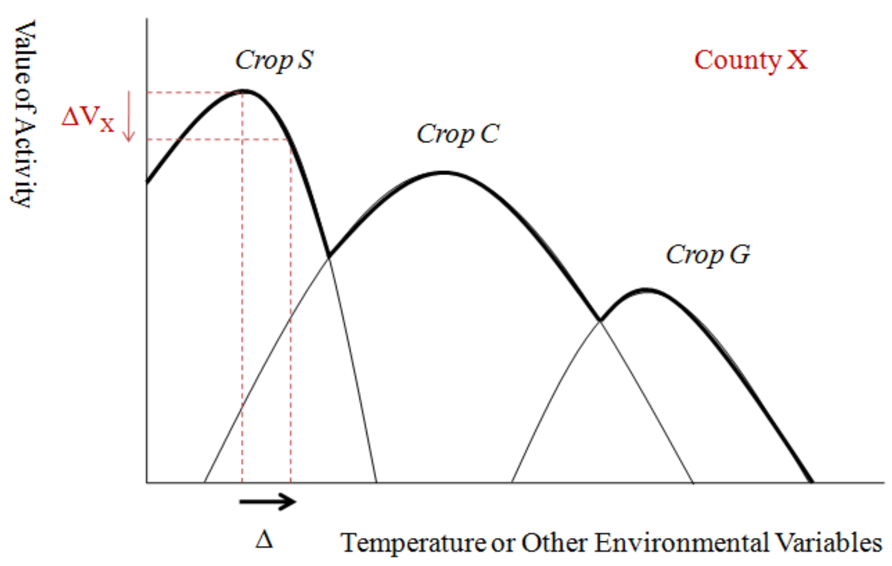
Previous research on the impacts of climate change on U.S. agriculture falls into two main highly correlated strands. The production function approach estimates crop yield losses under climate change using crop-growth simulation models. This approach has been criticized for ignoring adaptation and therefore overestimating the negative impacts of climate change. The Ricardian approach pioneered by Mendelsohn, Nordhaus, and Shaw (1994) regresses farmland value on climate and soil characteristics using cross-sectional data. Ideally, the cross-sectional

[1] In certain desert areas, the original farmland value is low. The model predicts a negative farmland value following these climate changes. This is an artifact of my linear model. Thus, in the paper, I report a -100% change on farmland value if the model predicts a loss exceeding the original value.

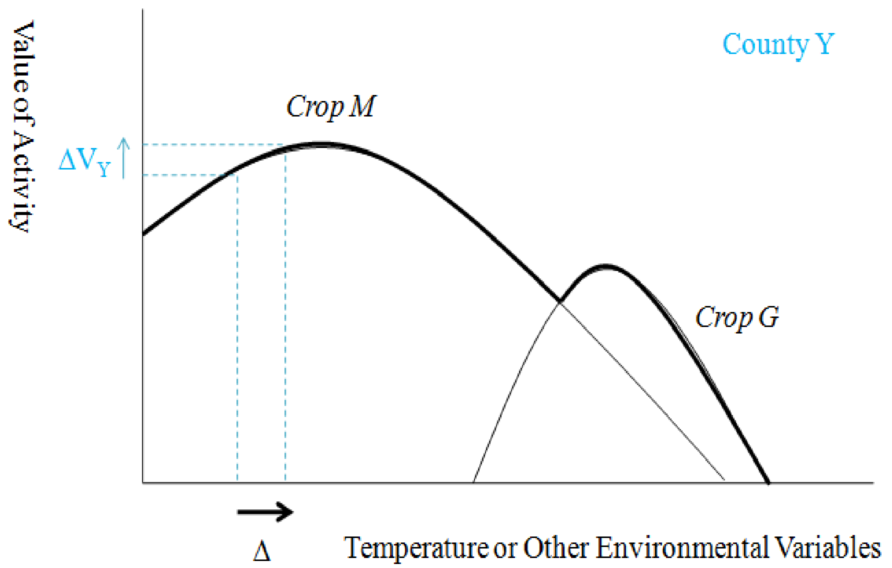
correlation between land value and climate should reflect the impact of climate change on U.S. agriculture in the long run, after farmers have fully adapted to their climate conditions.

Econometric approaches have gained popularity in the recent literature (Mendelsohn and Dinar 2009), including those incorporating heterogeneity in estimating the impacts of climate change on agriculture. Schlenker, Hanemann, and Fisher (2005) suggest that climate change has different impacts on irrigated and non-irrigated farmland. Deschenes and Greenstone (2007, 2012) and Massetti and Mendelsohn (2012) adopt a panel data approach to estimate the correlation between crop profits and weather, while controlling for unobserved county heterogeneity (e.g., irrigation and road network) that may bias cross-sectional estimates. Timmins (2006) derives a farmland value model from a discrete choice framework, showing that the impacts of climate change vary with crop shares. Thus, failing to control for crop choice will cause bias in the estimated coefficients on climate. However, none of these papers address the fundamental mechanisms of the heterogeneous impacts of climate change on U.S. agriculture, nor can they predict the potential benefits from technological change.

I contribute to the literature using econometric methods to infer the impacts of climate change on agriculture in several ways. Following Mendelsohn et. al. (1994), these contributions can be illustrated succinctly in graphical form. Figure 1.1 plots the profitability or value of different activities (growing crop *S*, *C*, or *G*) as a function of temperature or other environmental variables. The upper envelope (in bold) represents the maximum land value that can be achieved as temperature or other environmental variables change. Mendelsohn et. al. (1994) and most of its followers attempt to estimate this upper envelope in a reduced-form regression. My goal is to reveal its underlying structure, including how it may change with new crops and technology. Thus, I make four intellectual contributions in this paper.



(a) County X



(b) County Y

Figure 1.1 Heterogeneous Impacts of Climate Change in Two Hypothetical Counties

Note: Figures show different impacts of the same change in climate variables for two different counties. Before climate change, county X and Y are devoted to the production of crop *S* and *M* respectively. Since the same climate change makes the growing condition worse for crop *S* but better for crop *M*, farmland value will decrease in County X but increase County Y due to a different initial land-use choice.

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First, my model captures the heterogeneous impacts of soil and climate on U.S. agriculture, and I relate these impacts to underlying crop biological and physiological attributes. Consider Figure 1.1, which shows land value as a function of temperature in two counties: county X (panel a) and county Y (panel b). Suppose both counties have the same initial environmental conditions but different initial land-use choices due to other unobserved reasons. In Figure 1, land is devoted to the production of crop *S* in county X and to the production of crop *M* in county Y. Now suppose counties X and Y experience the same change in temperature. Farmland value decreases in county X because the temperature conditions worsen for crop *S*, while farmland value increases in county Y, since temperature conditions for crop *M* have improved. In reality, as in this example, crop attributes differ, and crop shares differ across counties, implying heterogeneous impacts of climate change on agriculture[2]. For example, drought will cause more damages in counties where less drought-tolerant crops are grown.

Second, I measure the economic values of a series of crop attribute-based adaptation strategies. See Figure 1.2. The shaded area in Figure 1.2(a) illustrate the benefit from land-use change. The shaded areas in Figure 1.2(b)-(d) measure the benefits from three adaptation strategies involving technological change—adopting new crops, adopting genetically modified major food crops, or uniformly applying chemicals to enhance climate favorable attributes of all crops. In (b), the shaded area measures the benefits from adopting a new crop, either an existing crop adopted at a new location or an entirely new crop that has never been grown anywhere. Similar to land-use switching, the farmer chooses the new crop because the new crop is more heat-tolerant and therefore better able to survive under temperature surplus. In (c), the shaded area measures the

[2] Mendelsohn argues that the use of quadratic functions of climate variables captures heterogeneous marginal effects of climate change on farmland value (personal communication). However, conditional on climate variables, the marginal effect of climate change is the same across counties in Mendelsohn, Nordhaus, and Shaw (1994). In this paper, the marginal effect of climate change varies by county, even conditioning on climate variables.

benefits from adopting a new crop variety, for example, a heat-tolerant variety. By definition, a heat-tolerant variety is more tolerant to heat than the usual variety and is considered to perform better under temperature surplus. In (d), the shaded area measures the benefits from applying chemicals such as a drought resistance spray developed by Syngenta to all existing crops. in this example, chemical sprays increase the drought tolerance and heat tolerance for a group of crops.

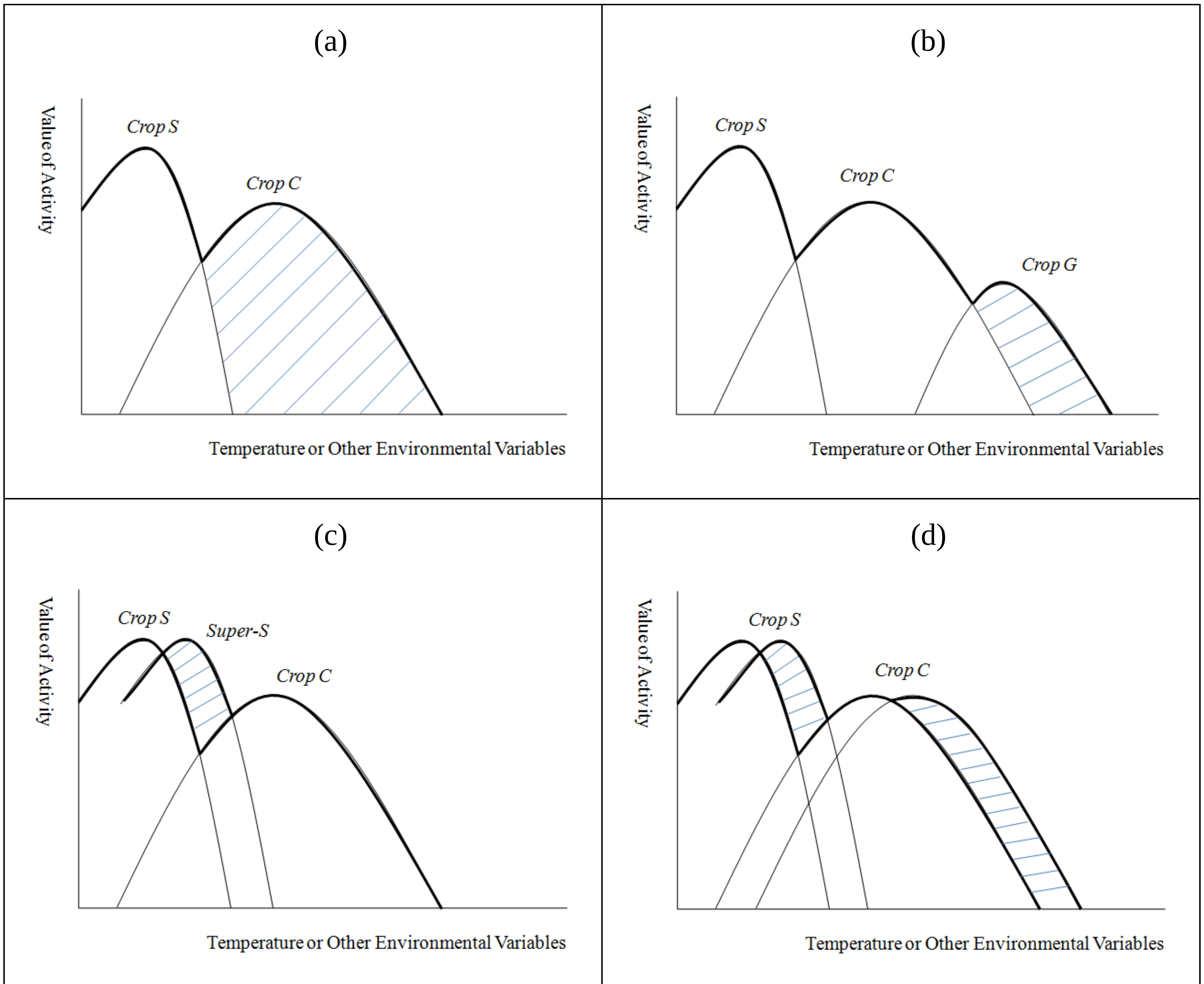

Figure 1.2 Benefits from Four Crop Attributes Related Adaptation Strategies

Note: Figures illustrate the economic values of four crop attribute related adaptation strategies. The shaded areas in panels (a)-(d) measure the values of the land-use switching, adoption of new crops, adoption of genetically modified crop varieties, and application of attribute-enhancing chemicals.

Third, I explicitly integrate the production-function approach and land-use choices into my econometric model of farmland value. Thus, I am able to study the impacts of climate change on crop yields, land-use choices, and farmland value in a single unified framework. The full model implicitly captures the reduced-form yield functions for each of the two-dozen field crops widely grown in the United States via interactions between soil and climate characteristics and crop attributes, and further includes interactions with crop prices to reflect the revenue impacts of climate change. Meanwhile, by explicitly modeling crop shares along with land values, the benefits of adaptation via land-use change can also be studied.

Fourth, I reconcile the use of cross-sectional and panel data in estimating the effects of climate change on U.S. agriculture. Dell, Jones, and Olken (2013) suggest a tradeoff to use cross-sectional versus panel data in estimating the impacts of climate change. The cross-sectional model uses average soil and climate data over a long period to capture the long-term impacts of soil and climate on farmland value; however, the estimates may be biased if omitted variables are correlated with soil and climate variables. The panel data approach uses short-term fluctuations in weather to identify the effects of weather on crop revenues or profits, while including fixed effects to control for unobserved county heterogeneity, such as irrigation. Though the potential omitted variable bias may be eliminated, this approach only allows short-term adaptation[3]. In my model, crop prices show great variation across time, while soil and climate show substantial variation across space. By interacting temporally varying national-level crop prices with spatially varying soil and climate characteristics, my model allows the coexistence of county fixed effects and with long-term climate structures.

The rest of the paper proceeds as follow: Section I develops the conceptual model of farmland value. Section II explains the empirical estimation strategy and describes the data on farmland

[3] Burke and Emerick (2013) define a 10-year average weather interval in estimating the impacts of climate change on agriculture.

value, soil and climate variables, crop prices, crop attributes, land-use choices, and other factors. Section III summarizes and interprets the main regression results. Section IV checks robustness. Section V simulates the impacts of climate change on agriculture. Section VI concludes with future research directions.

I. Farmland Value and Land-Use Choices

In this section, I derive a joint model of farmland value and land-use choices. Crop returns, which are the main determinant of farmland value and crop choice, are modeled as the products of prices and yields, less costs. Here, I assume that crop prices are exogenous. To relax this strict assumption, I would require adding a crop demand-side model to the already complex crop supply-side model. Since prices for staple food crops would likely to be impacted by climate change, this approach would be necessary to give plausible general equilibrium results. Even though the focus of this paper is the partial equilibrium impacts of climate change on crop supply, I maintain the price exogeneity assumption. However, I partially relax this assumption by performing a series of price sensitivity analysis, which I am able to do because crop prices are explicit in the model. Crop yields are modeled as a function of crop attributes and their interactions with soil and climate characteristics, reflecting the fact that crop yields respond differently to soil and climate conditions, depending on crop physiological attributes.

A. Land-Use Choices

Following Timmins (2006), the profit to producing crop j on parcel i in county c is given by:

$$U_{icj} = V_{cj} + \epsilon_{icj}, \tag{1}$$

$$V_{cj} = z_c \beta_j, \tag{2}$$

where V_{cj} is the mean value function of growing crop j in county c and ϵ_{icj} is a mean-zero parcel-specific error term. I take the mean value to be a linear function of local characteristics for county c (z_c) with a crop-specific parameter vector (β_j) that captures the monetary effects of location characteristics for a given crop[4]. As described in detail below, this crop-specific parameter vector will reflect differences in crop prices, as well as crop physiological attributes (e.g., stomata density and saturated fat content) and crop agronomy attributes (e.g., water-use efficiency and radiation-use efficiency) that affect a crop's yield response to soil and climate. For example, all else equal, a crop with a higher saturated fat content suffers less yield loss due to cold stress. Therefore, the negative coefficient on temperature deficiency will be smaller in magnitude for a crop with higher saturated fat content.

A farmer chooses crop j if $U_{icj} > U_{ick}$ for all crops $j \neq k$. That is, the farmer chooses the crop that maximizes profit on the parcel of land. The expected profit at anonymous parcel i in a given county c is given by:

$$E(U_{ic}) = E\left(\max_j U_{icj}\right). \tag{3}$$

[4] In general, this mean value function could also include various crop and county effects, which I suppress for now to ease exposition.

The above equation formally describes the profit envelope proposed in Mendelsohn, Nordhaus, and Shaw (1994), which posits that Ricardo's Law of Rent will hold, i.e., that land rent should equal the value of the land in its best use.

Following Small and Rosen (1981), McFadden (1974, 1981), and Dubin and McFadden (1984), if the idiosyncratic error ϵ_{icj} follows an i.i.d. Type-I extreme value distribution, then the expected profit at parcel i in county c is given by:

(4) $$E(U_{ic}) = E\left(\max_j U_{icj}\right) = \sigma \ln\left[\sum_{j\in J} \exp\left(V_{cj}/\sigma\right)\right] + constant,$$

where J represents the land-use choice set.

The probability that crop j is chosen at parcel i in county c is given by:

(5) $$\pi_{icj} = \frac{\exp[V_{cj}/\sigma]}{\sum_{l\in J}\exp[V_{cl}/\sigma]},$$

where $\sigma > 0$ is a scale parameter and $\sigma\pi/\sqrt{6}$ is the standard deviation of the parcel-specific error ϵ_{icj}.

By the Law of Iterated Expectations, the average profit in county c and the share of land devoted to crop j in county c are given by:

(6) $$E(U_c) = E_i[E(U_{ic})] = \sigma \ln\left[\sum_{l\in J}\exp(V_{cl}/\sigma)\right] + constant,$$

(7) $$s_{cj} = E_i\left[\pi_{icj}\right] = \frac{\exp[V_{cj}/\sigma]}{\sum_{l\in J}\exp[V_{cl}/\sigma]}.$$

As can be seen, the county aggregates in equations (6) and (7) are simply the familiar multinomial logit model applied to parcel-level data and aggregated to the county level. These equations facilitate econometric estimation using county-level aggregate data on land rents or farmland value[5], as is standard in the hedonic climate adaptation literature.

Note that I have not normalized the model with a specified base category in equation (7). Essentially, any land-use choice can be the base category. Practically, researchers usually choose the most common choice as the base category to facilitate the estimation of log odds model. Therefore, in this paper, for purposes of estimation, I specify pasture land as the base category, given its wide existence in U.S. counties.

Combining equations (6) and (7), it can be shown that:

(8) $$E(U_c) = V_{cj} - \sigma \ln\left(s_{cj}\right)^{6}.$$

Timmins (2006) argues that the land-use choice term should be explicitly added to the farmland model of Mendelsohn, Nordhaus, and Shaw (1994). Intuitively, as land-use share changes, the conditional expectation of the idiosyncratic error term changes. This is analogous to a standard bivariate selection model, in which treatment (in this case, crop choice) is chosen in part because of unobservables. Thus, the traditional approach implicitly assume that land-use share are fixed or that there is only one land-use. Adding the lns_{cj} term controls for this change in

[5] If farmer expects constant land rents over time, then farmland value is proportional to the current land rent.
[6] See Appendix 1.1 for derivation.

conditional expectations, in the same way that a selection model controls for bias by including the probability of selection as an additional control (Heckman 1979).

Another practical advantage of explicitly controlling for land-use choice is that it allows me to estimate the value of land-use change as an adaptation strategy, as in Figure 1.2a. The procedure is as follows. Step 1: Estimate farmland values under climate change, allowing land-use choice to change. Step 2: Estimate farmland values under climate change, holding land-use choice fixed. Step 3: Take the difference in farmland values with and without restrictions on land-use choice to obtain the value of land-use switching as an adaption strategy to climate change.

To see how my approach based on Timmins (2006) compares to that of Mendelsohn, Nordhaus, and Shaw (1994) and its followers, I weight equation (8) above by land-use shares to remove the crop specific subscript, yielding county average farmland values:

$$E(U_c) = z_c^{'}\bar{\beta}_c \; - \sigma\, \overline{\ln(s_c)} \tag{9}$$

where $\bar{\beta}_c = \sum_{j\in J} s_{cj}\beta_j$ is the crop share weighted average coefficients on county soil and climate characteristics and $\overline{\ln(s_c)} \; = \sum_{j\in J} s_{cj}\ln(s_{cj})$ is the share-weighted average of log share.

The above equation implies that land-use choice not only affects the level of farmland value but also the marginal effect of location characteristics on farmland value. Formally, I take the derivative of farmland value with respect to the location characteristics in equation (6) and directly obtain the marginal effect of location characteristic on farmland value:

$$\frac{\partial E(U_c)}{\partial z_c} = \frac{\partial \sigma \ln\left[\sum_{j\in J} \exp\left(V_{cj}/\sigma\right)\right]}{\partial z_c} = \sum_{j\in J} s_{cj}\beta_j = \bar{\beta}_c. \tag{10}$$

As can be seen, the marginal effects of location characteristics are different across counties. The underlying source of this heterogeneity is the different land-use choices across counties. For example, if there is a marginal increase in temperature surplus, then counties growing crops whose yields are more sensitive to heat will be more affected. This differs from Mendelsohn, Nordhaus, and Shaw (1994), which assumes that the marginal effect of climate change is the same across all U.S. counties, conditional on climate variables.

B. Crop Yields

The previous sub-section shows how land-use choice affects farmland value. This sub-section will show how crop attributes affect latent crop yields, conditional on soil and climate characteristics.

Following Anderson, Wang, and Zhao (2012), I re-specify the full crop specific profitability with crop dummy, county dummy, and crop-by-county dummy as follows:

$$V_{cj} = \boldsymbol{z}_c'\boldsymbol{\beta}_j + \varsigma_j + \delta_c + \xi_{cj}, \tag{11}$$

$$\boldsymbol{\beta}_j = p_j \mu_j^{max} \boldsymbol{\lambda}_j, \tag{12}$$

$$\boldsymbol{\lambda}_j = \left(\boldsymbol{\alpha}_o + \boldsymbol{\alpha}\boldsymbol{w}_j\right), \tag{13}$$

where: $\boldsymbol{z}$ is a $M \times 1$ vector of limiting geophysical and climatic factors in crop growth (e.g., temperature) that do not have close substitutes; ς is a crop fixed effect that measures unobserved variable crop costs and revenues under ideal growing conditions, minus fixed costs; δ is a county fixed effect that measures the unobserved value of non-limiting factors in crop growth (e.g. soil nutrients that can be easily substituted by man-made fertilizers); and ξ is crop by county effect that measures crop by county unobserved heterogeneity, such as the unobserved transportation cost to a local crop market. As shown in (12), the parameter $\boldsymbol{\beta_j}$ is a $M \times 1$ vector of crop-specific coefficients measuring the effects of soil and climate on crop revenue, which is modeled through an interaction between three terms: crop price (p), crop yield capacity (i.e., the maximum yield under non-stress conditions) (μ^{max}), and a $M \times 1$ vector of crop yield reduction parameters, which measures the percentage yield reduction under stress ($\boldsymbol{\lambda_j}$). As shown in (13), these parameters are in turn modeled as a linear function of N distinct crop attributes $\boldsymbol{w}$. Finally, $\boldsymbol{\alpha_o}$ is a $M \times 1$ parameter vector and $\boldsymbol{\alpha}$ is a $M \times N$ parameter matrix.

Crop attributes are defined as intrinsic biological properties of the crop that affect its reaction to limiting conditions. For example, root depth is a crop attribute. The deeper the root, the better the crop's ability to extract water from the soil. Therefore, under drought conditions, a crop with deeper roots can better avoid yield losses. In estimation, the numerical attributes are normalized such that the crop with the maximum value of an attribute takes a value of one, while the crop with the minimum takes a value of zero[7].

The yield reduction parameter is similar to the yield response factor that represents the effect of evapo-transpiration reduction on yield loss in FAO (2012). For example, if an element of $\boldsymbol{z}$ measures temperature surplus, then the corresponding parameter in α_o represents the yield reduction from temperature surplus for the crop with the lowest level of a heat tolerance measure

[7] The normalized attribute for crop j is given by $\tilde{a}_j = \frac{a_j - a_{min}}{a_{max} - a_{min}}$, where a_j, a_{min}, and a_{max} are the attribute values for crop j, the sample minimum, and the sample maximum.

(i.e., $w = 0$) and α represents the yield reduction that could have been avoided if the crop had a crop attribute $w > 0$.

To be consistent with the agronomy literature, I draw a three-step crop yield response to limiting growing conditions as in Figure 1.5. I use temperature as an example. As shown in Figure 3, when temperature falls below the minimum optimal temperature, the crop suffers a yield reduction from temperature deficiency; when temperature rises above the maximum optimal temperature, the crop suffers a yield reduction from temperature surplus; when temperature happens to be in the optimal range, the crop reaches its yield capacity. The slope from the origin to the minimum optimal temperature measures how sensitive the crop is to temperature deficiency. The steeper this slope, the less tolerant the crop is to temperature deficiency. Similarly, the slope from the maximum optimal temperature to the horizontal axis measures how sensitive the crop is to temperature surplus. The steeper this slope, the less tolerant the crop is to temperature surplus[8]. In other words, the impact of temperature surplus is the corresponding element of $\boldsymbol{\alpha}_o + \boldsymbol{\alpha}\boldsymbol{w}_j$, which depends on a series of crop attributes (e.g., saturated fat content and maximum radiation use efficiency) that are correlated with heat tolerance.

C. Farmland Value

Plugging the model of crop revenues and costs in equations (11)-(13) into the model of land rent in equation (8) yields my full model:

[8] The yield reduction parameters are motivated in part by Schlenker and Roberts (2009), who plot percent crop yield responses to random temperature variations. Crop yields for corn and soybeans increase slightly as temperature increases, up to 29-30°C, after which crop yields drop sharply as temperature increases. Thus, I conceptualize yields as percent decreases below maximum yield, as a result of heat (or cold, or drought) induced plant stress.

$$(14)\quad E(U_c) = \{p_j[\underbrace{\mu_j^{max}(\boldsymbol{z}_c'\boldsymbol{\alpha}_o + \boldsymbol{z}_c'\boldsymbol{\alpha}\boldsymbol{w}_j)}_{\text{Latent Yield}}] + \varsigma_j + \delta_c\} - \sigma \ln\underbrace{(s_{cj})}_{\text{Land-Use Choice}} + \xi_{cj}.$$

The above equation shows the formation of land rent. At the beginning of a growing season, the farmer has an expectation about the upcoming year's yield from growing crop j. As a price-taker, he estimates this year's profit of growing crop j by multiplying expected price and expected yield of crop j; as a rent seeker, he chooses the land-use which yields the highest profit. If he wishes to sell his land, then the land value is the present discounted value of the expected future stream of land rents. If we assume that the real interest rate is constant and farmer expects constant land rents over time, then farmland value is proportional to the annuity (i.e., the current land rent).

Rearranging the above equation gives:

$$(15)\quad E(L_c) = \frac{1}{\kappa} p_j \mu_j^{max} \boldsymbol{z}_c'\boldsymbol{\alpha}_o + \frac{1}{\kappa} p_j \mu_j^{max} \boldsymbol{z}_c'\boldsymbol{\alpha}\boldsymbol{w}_j - \sigma ln s_{cj} + \varsigma_j + \delta_c + \xi_{cj},$$

where $E(L_c)$ is the average farmland value in county c and κ is the capitalization rate.

This equation reflects the evolution of the Ricardian Approach for farmland valuation. Mendelsohn, Nordhaus, and Shaw (1994) and followers regress farmland values on soil and climate characteristics to infer the homogeneous economic impacts of climate change on the agricultural sector, which is captured by the first term in the above equation if I normalize $p_j \mu_j^{max}$ to unity. Schlenker, Hanemann, and Fisher (2005) estimate the Ricardian model separately for irrigated counties and non-irrigated counties, suggesting heterogeneous impacts of climate change on farmland values by irrigation choice. These impacts depend on underlying crop production function and crop choice aggregated at the county level, which is captured by the fifth term. Deschenes and Greenstone (2012) employ panel data approach to eliminate the bias caused by county heterogeneity (e.g. irrigation and road network), which is captured by the fifth term. Timmins (2006) shows that it is important to control for the land-use choice, especially when the cost of adaptation is prohibitive and the farmer cannot adjust land-use choice quickly in the short run. This issue is captured by the third term. Timmins (2006) also allows for unobserved crop and crop-county heterogeneity, which is captured by the fourth and sixth terms in the above equation. Lastly, Anderson, Wang, and Zhao (2012) show in the context of crop choices that crop-specific coefficients can be modeled as a function of observable crop attributes, which is captured by the second term in the above equation—this paper's contribution to the Ricardian Approach, which allows me to evaluate the benefits of crop adaptation in farmland value formation and therefore the heterogeneous impacts of climate change on agriculture.

II. Data and Empirical Estimation

A. Data

Farmland value at the beginning of the growing season depends on farmers' expectation about crop prices and crop yields and how they allocate land to different uses. I obtain county average farmland value ($ per acre, including farmland value and buildings)[9] from the U.S. Census of Agriculture for 1978, 1982, 1987, 1992, 1997, 2002, and 2007 for 3,116 counties. I collected cash

[9]Land value is not separately collected by USDA, so I follow virtually all previous studies in this literature and use farmland value and buildings as the dependent variable.

rent data from the U.S. Census of Agriculture for 1997, 2002, and 2007. I obtain planted acreage in each county from NASS surveys in corresponding census years. Likewise, I obtain the national-level crop prices and national-level cattle price from NASS surveys in corresponding census years. These are used as proxies for expected prices and planted acreage in each county for twenty-three field crops[10]. Yield capacity (i.e., maximum yield) by crop is obtained by the following two steps: first, average the time series county-level observed yield for each crop in the 1970-2012 NASS surveys; second, take the maximum of the average yield across counties obtained from the first step. Crop attributes are from USDA Plant Characteristics Database and the agronomy literature. County-level soil data are constructed from soil maps which are downloaded from the Soil Survey Geographic Database (SSURGO). County-level climate data are constructed from daily maximum and minimum temperature and monthly rainfall which are from Schlenker and Roberts (2009)[11]. Their weather data were collected on 4 km×4 km grid cells monthly over the United States for 1950-2005, interpolated to daily maximum and minimum temperature, and aggregated by averaging to county-day level, weighting grid cells by their land in agricultural use. The selection and construction of crop attributes and climate variables are summarized below. Detailed data selection and construction can be found in Appendices 1.2 and 1.3.

[10] Total harvested acres of field crops are for alfalfa, barley, beans, corn, cotton, flaxseed, lentils, mustard, oats, peanuts, peas, potatoes, rapeseed, rice, rye, safflower, sorghum, soybeans, sugarcane, sugarbeets, sunflower, tobacco, and wheat, which consist of one third of farmland, leaving the remaining two thirds—CRP and pasture (either permanent pasture or cropland pastured)—in the base category of the multiple discrete choice model.

[11] Auffhammer et. al. (2013) provide a detailed documentation of weather data sources.

Farmland Value . — Figure 1.3 shows the temporal and spatial variation in average farmland value over the seven census years. Figure 1.4 shows the temporal correlation between average farmland value and major crops' maximum revenue (crop price × maximum crop yield). As can be seen, there is a strong correlation between farmland value and major crop prices over the consecutive census years. For example, when crop prices are high in 1978 and 2007, farmland values are high in these years. When crop prices are low in 1987 and 1992, farmland values are low in these years. Holding crop prices constant, the variation in farmland value across space is mainly driven by spatial variation in soil and climate characteristics.

Soil Variables. — Available water capacity (shortened as "moisture"), pH, water erosion factor (KFF), and slope are obtained from Soil Survey Geographic Database (SSURGO).

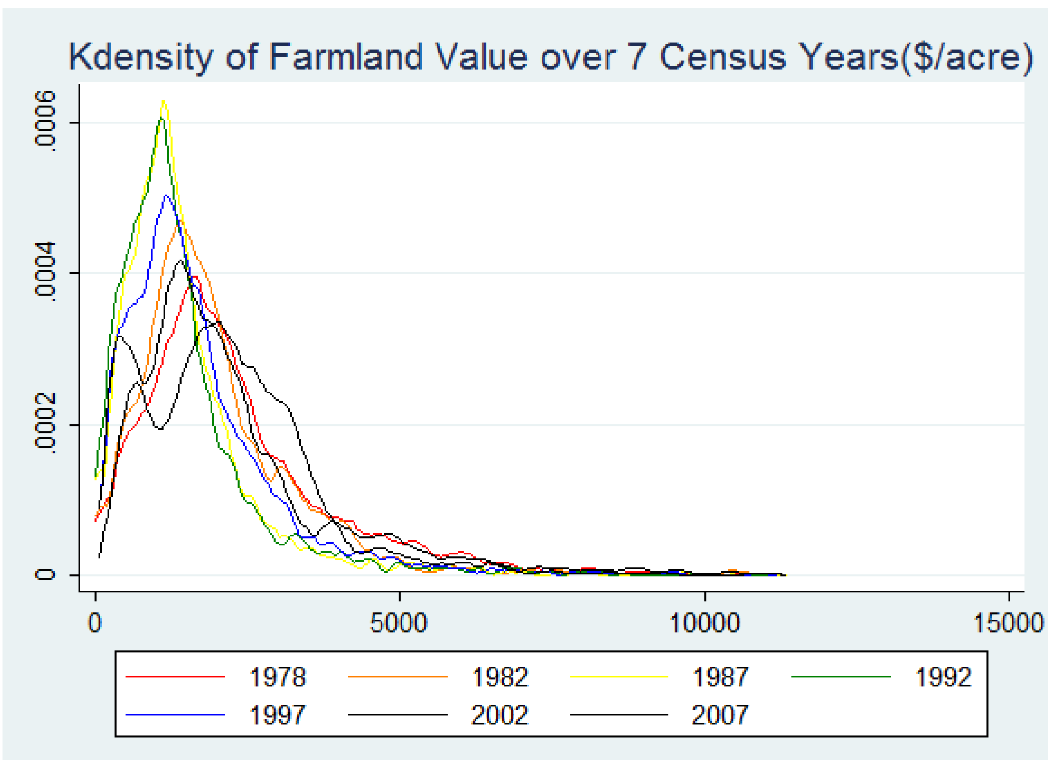

Figure 1.3 Temporal and Spatial Variation in Farmland Values

Note: Figure shows the kernel density of farmland value over the most recent seven census years. Each color represents a different census year. The figure shows great variation in farmland value across both time and space.

(a) (b)

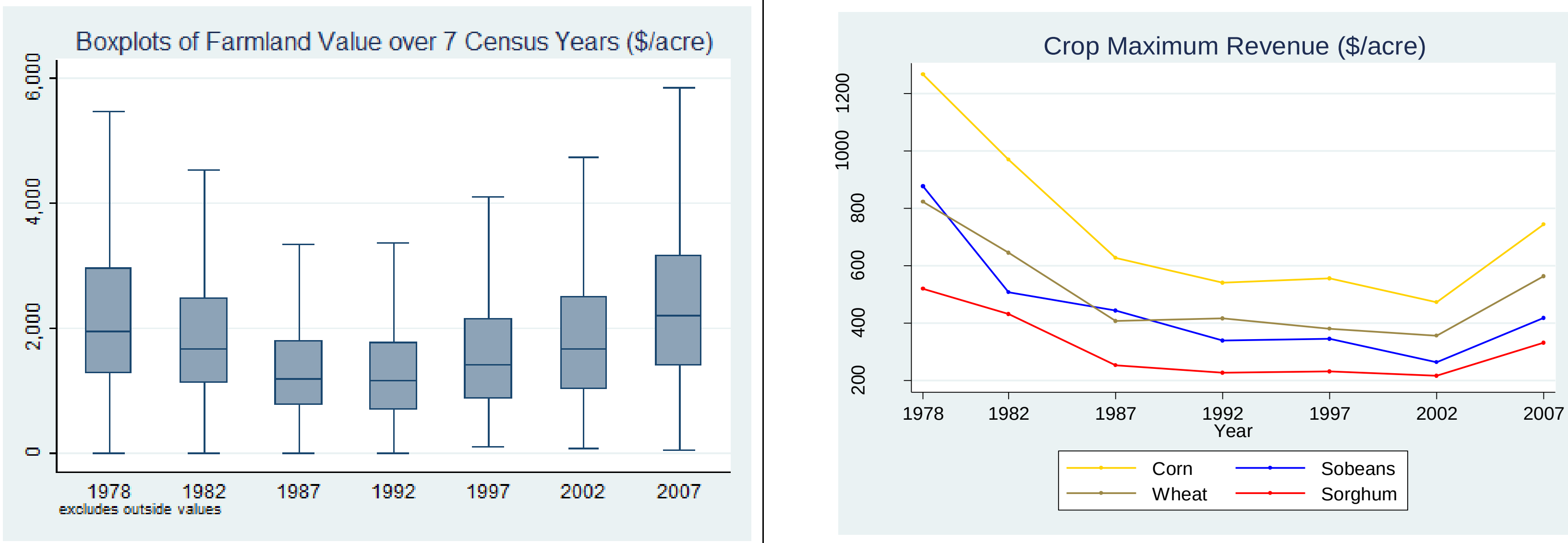

Figure 1.4 Temporal Correlation between Farmland Value and Crop Prices

Note: Figures show a positive correlation between farmland value and crop prices over seven census years. In panels (a) and (b), farmland value and crop prices follow the same pattern: decrease from 1978 to 1992 and increase from 1992 to 2007.

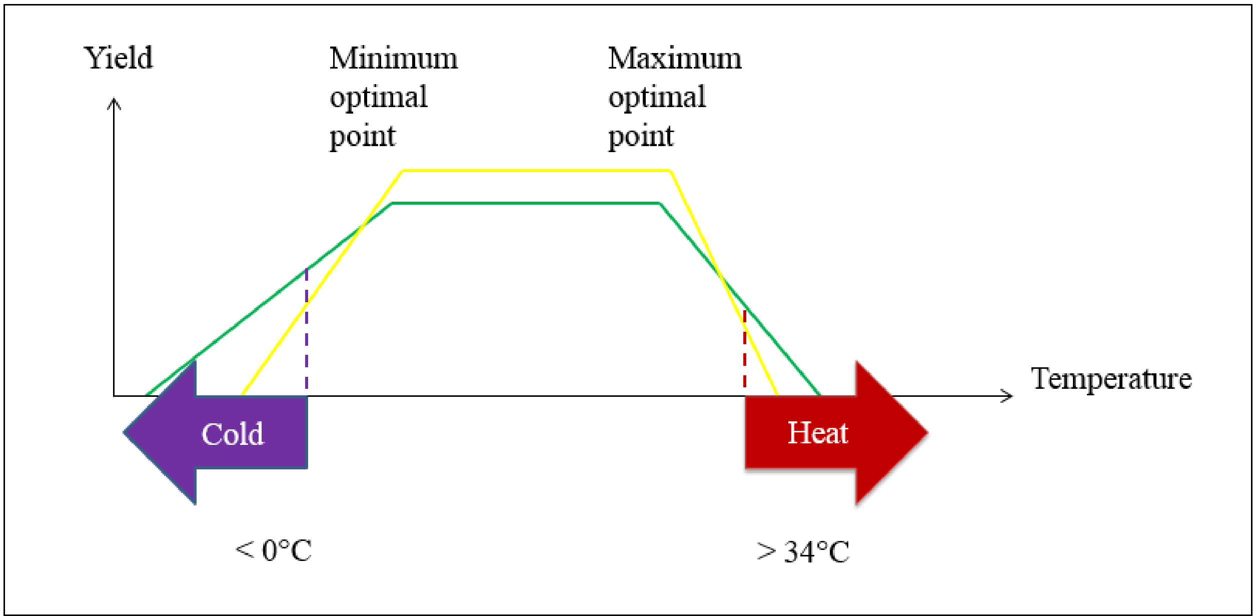

Figure 1.5 Crop Yield Response to Limiting Inputs and Construction of Heat and Cold

Note: Figure shows yield responses to limiting growing conditions for two hypothetical crops—yellow crop and green crop. Under cold conditions, the yield response of the green crop is less sensitive to cold than the yield response of the yellow crop.

Climate Extremes. — I construct two temperature extremes—temperature deficiency (shortened as "cold") and temperature surplus (shortened as "heat"), as in Figure 1.5. If temperature falls in a stress range, then all crops are either under temperature deficiency or under temperature surplus. Temperature deficiency is defined as the sum of daily degree days below 0°C, and temperature surplus is defined as the sum of daily degree days above 34°C during April to September. Similarly, I construct two rainfall extremes—rainfall deficiency and rainfall surplus. Rainfall deficiency (shortened as "drought") is defined as the sum of daily rainfall if daily rainfall is below 0.2cm, and rainfall surplus (shortened as "flood") is defined as the sum of daily rainfall if daily rainfall is above 1.7cm during April to September. Since climate is a long term phenomenon, I average the 30 years of temperature extremes and rainfall extremes prior to each corresponding census year and use them as the expected climate extremes in the census year. For example, the average degree days below 0°C during 1952-1981 is used as the expected degree days below 0°C in 1982. Figure 1.6 shows the spatial and temporal variation in climate extremes. Though the histograms exhibit some temporal variation, the variations over space dominates the variation over time for these climate extremes. Table 1.1 shows the descriptive statistics of farmland value, soil characteristics, and climate extremes.

Crop Attributes . — Table 1.2 lists the attributes chosen to reflect drought tolerance (water use efficiency, root depth, and stomata density), flood tolerance (height and root type - fibrous or taproot), cold tolerance (growing season length and saturated fat content), heat tolerance (radiation-use efficiency and saturated fat content), pH tolerance, and photoperiod (i.e., physical reaction to day length). These attributes collectively measure the effects of extreme climate stresses (e.g., drought, excess water, cold, and heat) on yield losses.

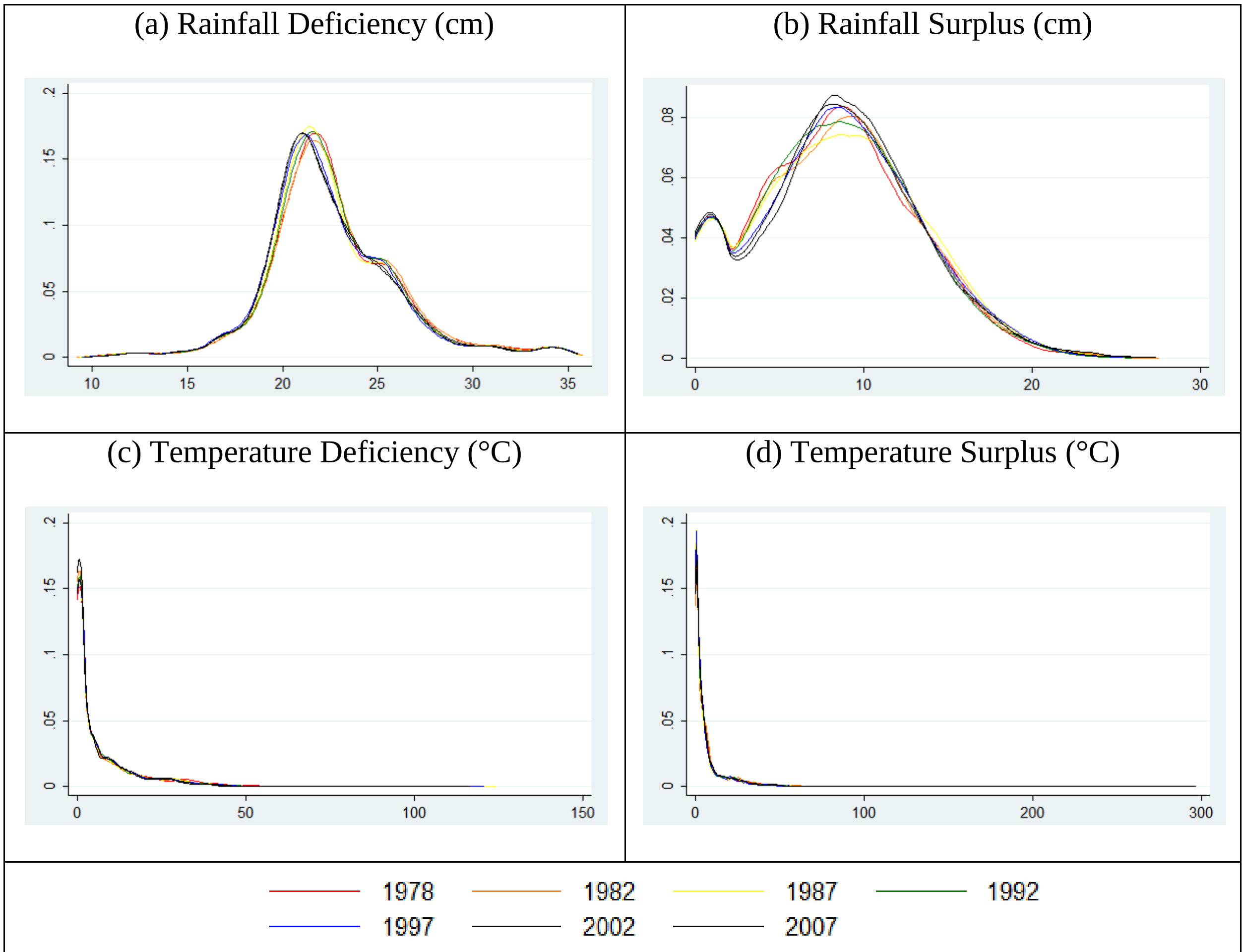

Figure 1.6 Spatial Variation and Temporal Variation in Climate Extremes

Note: Figures show the kernel density of four climate extremes: rainfall deficiency, rainfall surplus, temperature deficiency, and temperature surplus over the most recent seven census years. Each color represents a different census year. As can be seen, climate extremes show little variation over time but great variation over space.

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Table 1.1 Descriptive Statistics on Climate Extremes and Soil Characteristics

Variable	Mean	SD	Min	Max
Farmland Value ($/acre)	2026.05	2671.63	0	251941
Rainfall Deficiency (Rainfall Below 0.2cm) (cm)	22.6	3.44	9.2	36
Rainfall Surplus (Rainfall Above 1.7cm) (cm)	8.29	4.86	0	28
Temperature Deficiency (Degree Days Below 0°C) (°C)	6.29	10.06	0	113
Temperature Surplus (Degree Days Above 34°) (°C)	6.71	14.79	0	297
Available Water Capacity (%)	14.8	2.49	3	23
pH	6.37	1.06	4.6	9
Water Erosion (KFF) (%)	32.29	7.2	3	58
Soil Slope (degree)	3.92	3.14	0	35
Observations	20983			

Note: Table shows the summary statistics for un-weighted farmland value, climate extremes and soil characteristics. Farmland value is in 2002 dollars. Rainfall Deficiency, Rainfall Surplus, Temperature Deficiency, and Temperature Surplus are daily measures accumulated over April-September in each year and then averaged over 30 years prior to each census year.

Table 1.2 Crop Attributes

Crop	WUE index	Roots (inches)	Stomata (# per mm^2)	Height (feet)	Fibrous Root	Season (days)	Saturated Fat (%)	RUE (g per MJ)	Long –Day Crop	Min. pH	Max. pH
Alfalfa	0.427	24	178.5	2	0	90	0.069	1.1	1	6	8.5
Barley	0.875	10	77.5	2.5	1	90	0.155	1.6	1	5	8.5
Beans	0.798	6	160.5	3	1	120	0.109	0.82	0	6	6.9
Corn	1.000	8	103	8	1	90	0.105	2	0	5.5	7.5
Cotton	0.604	16	150	6	0	365	0.209	1.5	0	6	7
Flaxseed	0.208	2	91	2.6	0	100	1.180	1.7	1	5	8
Lentils	0.682	5.5	240	1.8	0	160	0.057	1.14	1	6	8
Mustard	0.323	12	220	3	0	125	0.010	1.92	1	5	8
Oats	0.347	8	47.5	2	1	90	0.387	1.45	1	5.3	8.5
Peanuts	0.359	20	161	1.3	0	265	2.201	1.2	0	5	7.5
Peas	0.583	6	158.5	3	1	95	0.124	1.5	0	5.5	6.5
Potatoes	2.095	12	134	2	1	110	0.026	1.65	1	5.2	6.8
Rapeseed	0.289	6	250.5	4	0	130	0.437	1.4	1	6	7.2
Rice	1.097	5	705	3.4	1	120	0.045	1.35	0	5.5	6.5
Rye	0.349	8	154.5	3.5	1	110	0.063	2.1	1	4.5	8.2
Safflower	0.349	10	163.75	3	0	120	1.186	1.45	1	6	7
Sorghum	1.143	12	142.4	4	1	90	0.147	1.75	0	5.5	7.5
Soybeans	0.642	8	113	3	0	140	0.929	1	0	5.5	7.8
Sugarbeets	0.004	5	172.75	2	0	120	0.009	1.9	1	6.3	7.5
Sugarcane	1.281	24	112.76	12	1	365	0.000	1.75	0	4	7
Sunflower	0.510	8	147.5	9	0	80	1.435	1.85	0	5.5	7.8
Tobacco	0.836	24	120	6	0	120	0.000	1.52	0	5.7	7.8
Wheat	0.717	18	45	3.3	1	100	0.161	1.65	1	5.5	8

Note: This table shows the matrix of crop physiological attributes for the widely grown twenty-three field crops in the United States. The data are collected from two major sources: USDA Plant Characteristics Database and agronomy/botany journal articles, which are explained in detail in Anderson, Wang, and Zhao (2012).

Crop Shares. — Table 1.3 summarizes county level crop shares when crops are planted with positive acreages at the county level. Five crops—sugarcane, corn, soybeans, rice, and cotton—are grown in large shares in relative few counties. In counties where sugarcane is planted, on average, sugarcane occupies 23.3% (SD=22%) of farmland. In counties where soybeans are planted, on average, soybeans occupy 15.4% (SD=14.9%) of farmland. In counties where corn is planted, on average, corn occupies 12.6% (SD=14.6) of farmland. In counties where rice is planted, on average, rice occupies 8.8% (SD=8.8%) of farmland. In counties where cotton is planted, on average, cotton occupies 8.3% (SD=9.9%) of farmland.

Crops with zero shares are dropped in the main analyses. By doing so, I make a strong assumption that the crop share data are missing at random. Though simple, the dropping method of missing crop shares may cause sample selection bias. Some researchers add small number to the missing data, however, Young and Young (1975) propose that adding small numbers make the model less robust since the model becomes sensitive to the chosen small numbers. Therefore, I conduct a series of alternative approaches to deal with the missing crop shares in the robustness check section.

B. Fixed Effect Estimation

Econometric Model. — The empirical model follows naturally from the conceptual model and the panel data structure. I specify the main econometric model as follows:

$$(16) \quad V_{ct} = \frac{1}{\kappa} p_{jt} \mu_j^{max} \boldsymbol{z}'_{ct} \boldsymbol{\alpha}_o + \frac{1}{\kappa} p_{jt} \mu_j^{max} \boldsymbol{z}'_{ct} \boldsymbol{\alpha} \boldsymbol{w}_j - \sigma ln s_{cjt} + \varsigma_j + \delta_c + \xi_{cjt},$$

where c indexes counties and t indexes years.

Table 1.3 County-Level Crop Shares

Variable	Observations	Mean	SD	Min	Max
Alfalfa	17159	3.36%	4.24%	0.00%	33.15%
Barley	6480	1.50%	3.04%	0.00%	34.69%
Beans	4431	0.68%	2.13%	0.00%	27.18%
Corn	16928	12.63%	14.62%	0.00%	74.12%
Cotton	3081	8.29%	9.92%	0.00%	64.74%
Flaxseed	513	0.76%	1.07%	0.00%	8.87%
Lentils	119	2.14%	3.11%	0.00%	15.05%
Mustard	112	0.35%	0.42%	0.01%	2.00%
Oats	12441	0.97%	1.70%	0.00%	20.88%
Peanuts	1871	3.27%	4.86%	0.00%	25.67%
Peas	1249	0.45%	1.12%	0.00%	12.55%
Potatoes	5272	0.61%	2.40%	0.00%	50.34%
Rapeseed	277	1.55%	3.24%	0.01%	25.60%
Rice	740	8.76%	8.83%	0.05%	36.98%
Rye	4035	0.25%	0.43%	0.00%	7.96%
Safflower	330	0.57%	1.02%	0.00%	7.42%
Sorghum	8166	2.01%	4.09%	0.00%	53.04%
Soybeans	12313	15.36%	14.85%	0.00%	86.58%
Sugarbeets	796	2.16%	2.97%	0.00%	21.61%
Sugarcane	157	23.24%	21.76%	0.00%	71.40%
Sunflower	1477	1.69%	3.08%	0.00%	25.02%
Tobacco	3099	1.29%	1.59%	0.00%	11.02%
Wheat	15561	5.57%	8.00%	0.00%	64.80%

Note: Table shows un-weighted county-level crop share for the twenty-three field crops widely grown in the United States. These statistics are conditioned on a county having non-zero crop shares (i.e., counties with zero shares for a given crop are excluded).

I model crop returns as an explicit function of crop revenues and control for costs implicitly using crop dummies. This specification is consistent with empirical evidence. Duffy (2012) finds that gross income, which is captured by the first and second terms, is the major driving factor of farmland value and that gross income is a better predictor than net income for farmland value. Therefore, I impose fixed production cost and control for it with crop dummies. Another reason to focus on the crop revenue is that both crop price and crop yield are directly correlated with climate, while production cost is indirectly correlated with climate at best. I also include county dummies to control for unobserved institutional factors and other time-invariant factors that affect land value. Later, I check whether the coefficients are robust across different specifications by adding: crop × region dummies to control for the local crop choice set; year dummies to control for aggregate effects affecting all crops in all counties in a single year; crop × year dummies to control for changes in crop technology, subsidies, and input costs, and finally socioeconomic variables to capture the effects of population density, per capita income, and other local, time-varying factors on farmland value.

Identification . — As we have seen from the data section, farmland value exhibits both temporal and spatial variation. It is intuitive that annual crop prices are the main driving factor contributing to the temporal variation in farmland value (and land-use choices), while the soil and climate conditions interacted with crop physiological attributes are the main driving factor contributing to the long-term spatial variation in farmland value (and land-use choices). Therefore, I allow farmland value to vary over years and space, and the model uncovers how farmland value (and land-use choices) is determined by the joint effects of temporal crop prices and spatial latent crop yields induced by soil and climate conditions.

In the main regression, I only include crop dummies and county dummies to control for the unobserved cross-sectional factors. The identification of the coefficients relies on the assumption that crop prices are the only factor driving temporal variation in farmland value, both directly on crop revenue and indirectly on land-use choices. I will relax this assumption in the robustness checks section. This hybrid variation helps to bridge the panel-data approach and the cross-sectional approach in estimating the impacts of climate change on agriculture.

Since many adaptation strategies involve changes in crop physiological attributes, the identification of technological change is captured by the cross-species variation in crop attributes. Though there is substantial technological advances within a crop over years, data is not widely available. Therefore, I assume that the temporal changes within a crop is significantly smaller than the variations across crops to facilitate the identification of technological change. Nevertheless, the assumption of time-constant crop attributes is mainly a convenience for the purpose of econometric identification—not realistic in real world.

Endogeneity of Land-Use Choice. — We can infer from equations (7) and (11) that ξ_{cjt} is a determinant of s_{cjt}. Thus, OLS will not consistently estimate σ. To deal with the potential endogeneity of s_{cjt}, I apply a two-stage least square (2SLS) approach to estimate σ. I instrument for $\ln(s_{cjt})$ using the revenue weighted average of *other* crops' attributes interacted with climate extremes and soil characteristics, which may proxy for the average return of other crops[12].

Since these instruments show up in the denominator of s_{cjt} (see equation 7), they are mechanically correlated with $ln\ s_{cjt}$. This is the first criterion for a valid instrument. Intuitively, if land is more suitable to growing other crops, then the likelihood of growing a given crop should be lower. The second criterion for a valid instrument requires the instruments to be uncorrelated with the unobserved crop by county effects. Crop prices are determined nationally, so they should not be influenced by any single crop-county unobservable. Climate extremes and soil conditions in a county are long term and should not be influenced by the crop-county unobservable. Crop attributes are intrinsic and should not be influenced by the crop-county unobservable. A concrete example of the unobserved crop by county effects is a local market of a given crop, say sugarcane.

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[12] The mathematical formula for the instrument is given by: $\sum_{l\in J\setminus j}\{s_{cl} \times p_l[\mu_l^{max}(\boldsymbol{z}_c'\boldsymbol{\alpha}_o + \boldsymbol{z}_c'\boldsymbol{\alpha}\boldsymbol{w}_l)]\}$.

The existence of the local sugarcane market will induce more sugarcane production in nearby counties, relative to counties far away. However, we do not expect the existence of this local sugarcane market to be correlated with another crop's national level price, another crop's intrinsic attributes, and local soil and climate characteristics.

To allow spatial correlation between among crops within a county, I cluster the standard errors by county. Note that researchers that use the cross-sectional reduced-form Richardian approach usually cluster the standard errors of the model at state level to control for the spatial correlation between counties (Schlenker, Hanemann, and Fisher 2005) and apply GMM to explicitly model the spatial correlation (Conley 1999, Williams, Shaw, and Mendelsohn 1998, Schlenker, Hanemann, and Fisher 2006, Wooldridge 2010).

III. 2SLS Estimation Results

The first stage results are shown in Table 1.4. The joint *F*-statistic of the excluded variables is 31.57, so we do not worry much about weak instruments in this context. Table 1.5 presents the main regression results. The coefficient on log (crop share) is \$1,426 per acre. This implies that the standard deviation of ϵ_{icj} is $\frac{\pi}{\sqrt{6}} \times \$1{,}426 = \$1{,}828$, corresponding to 91% of the un-weighted average farmland value. The remaining coefficients estimated from the main regression directly correspond to $\frac{1}{\kappa} \cdot \alpha_o$ and $\frac{1}{\kappa} \cdot \alpha$ that represent the effects of the interactions between crop attributes and soil and climate characteristics on crop yield in perpetuity. Given my normalization of crop attributes, $\frac{1}{\kappa} \cdot \alpha_o$ reflects the impacts of soil and climate conditions on yield for a crop that has the lowest value of a crop attribute, while $\frac{1}{\kappa} \cdot \alpha$ reflects the changing impacts of soil and climate conditions on yield as crop attributes change from the lowest to the highest. These coefficients, along with crop attributes (w), can then be used to construct crop yield reduction parameters λ and crop differential returns β, which are both crop-specific.

A. Adaptation to Climate

As can be seen from Table 1.5, a one cm increase in *rainfall deficiency* (increase in drought) decreases crop yield by 14.62% for the most drought intolerant crop but decreases yield less for other crops, depending on their WUE, root depth, and stomata density. The crop yield reduction parameters (λ) for drought are ranked and presented in Panel A in Table 1.6. The results show that the five most drought-intolerant crops are flaxseed, sugarbeets, rapeseed, oats, and rye, while the five "most drought-tolerant" crops are potatoes, sugarcane, tobacco, sorghum, and rice, raising a red flag to most agronomists since potatoes, sugarcane, and rice are very sensitive to drought (FAO 1996, 2012) and for this reason they are typically irrigated. Note therefore that these parameters cannot be interpreted as yield responses to drought because of the omitted variable—irrigation. Since irrigation has a positive effect on crop yield and is positively correlated with drought severity, it makes perfect sense that the parameters on drought absorb the effect of irrigation and therefore are biased upward. This is also evident from the unexpected sign on the interaction between drought and WUE. When there is not sufficient rainfall, farmers are expected to reduce the production of crops with high WUE, which are more sensitive to drought. However, if irrigation technology is well established, farmers tend to grow more water-intensive crops to boost yield (Hornbeck and Keskin 2013).

Table 1.4 Determinants of Land-use Choice − First Stage

Variables	I	Variables	II
Drought	-0.0113		
	(0.0007)		
Drought×WUE	0.0070	Drought×WUE (other)	-0.0029
	(0.0007)		(0.0006)
Drought×Roots	0.0068	Drought×Roots (other)	0.0017
	(0.0006)		(0.0003)
Drought×Stomata	0.0069	Drought×Stomata (other)	0.0020
	(0.0015)		(0.0007)
Flood	-0.0062		
	(0.0002)		
Flood×Height	0.0139	Flood×Height (other)	0.0017
	(0.0005)		(0.0002)
Flood×Fibrous Root	0.0017	Flood×Fibrous Root (other)	-0.0011
	(0.0002)		(0.0002)
Cold	0.0063		
	(0.0002)		
Cold×Season	-0.0545	Cold×Season (other)	0.0000
	(0.0017)		(0.0001)
Cold×Saturated Fat%	-0.0155	Cold×Saturated Fat% (other)	-0.0007
	(0.0012)		(0.0003)
Heat	-0.0009		
	(0.0002)		
Heat×RUE	0.0015	Heat×RUE (other)	0.0001
	(0.0003)		(0.0000)
Heat×Saturated Fat%	-0.0001	Heat×Saturated Fat% (other)	-0.0006
	(0.0003)		(0.0002)
Sunshine	0.0009		
	(0.0002)		
Sunshine×1[Long-Day Crop]	0.0014	Sunshine×1[Long-Day Crop]	0.0008
	(0.0001)		(0.0001)
Sunshine×RUE	-0.0032	Sunshine×RUE (other)	-0.0004
	(0.0002)		(0.0001)
Moisture	0.0196		
	(0.0017)		
Moisture Squared	-0.0000		
	(0.0000)		
Moisture×WUE	-0.0157	Moisture×WUE (other)	-0.0003
	(0.0010)		(0.0007)
Moisture×Roots	-0.0085	Moisture×Roots (other)	0.0002
	(0.0009)		(0.0003)

Table 1.4 (cont'd)

Moisture×Stomata	-0.0138	Moisture×Stomata (other)	-0.0016
	(0.0023)		(0.0010)
pH	0.0309		
	(0.0034)		
pH Squared	-0.0033		
	(0.0003)		
pH×1[pH<Min. pH]	-0.0004	pH×1[pH<Min. pH] (other)	-0.0003
	(0.0002)		(0.0001)
pH×1[pH>Max. pH]	0.0003	pH×1[pH>Max. pH] (other)	0.0001
	(0.0002)		(0.0000)
Water Erosion	0.0002		
	(0.0001)		
Water Erosion×Roots	-0.0019	Water Erosion×Roots (other)	-0.0000
	(0.0003)		(0.0001)
Water Erosion×Height	0.0019	Water Erosion×Height (other)	0.0001
	(0.0004)		(0.0003)
Slope	-0.0039		
	(0.0003)		
Slope×Roots	0.0118	Slope×Roots (other)	0.0020
	(0.0008)		(0.0007)
Slope×Height	-0.0170	Slope×Height (other)	-0.0033
	(0.0015)		(0.0014)
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		

Note: Table shows the first-stage results of log (crop share) regressed on the maximum revenue weighted average of other crops' attributes interacted with soil and climate characteristics (the instruments), other exogenous variables, and controls. A joint F-statistic on the excluded variables is 31.57.

Table 1.5 Determinants of Agricultural Land Value − 2SLS

Variables	I	Variables	II
Log Crop Share	-1,425.75		
	(46.97)		
Drought	-14.62	Moisture	42.42
	(1.06)		(2.63)
Drought×WUE	12.72	Moisture Squared	-0.03
	(0.71)		(0.07)
Drought×Roots	7.13	Moisture×WUE	-32.27
	(0.74)		(1.20)
Drought×Stomata	3.81	Moisture×Roots	-21.88
	(2.02)		(1.21)
Flood	-9.68	Moisture×Stomata	-21.44
	(0.42)		(3.10)
Flood×Height	20.11	pH	49.31
	(0.90)		(5.22)
Flood×Fibrous Root	4.90	pH Squared	-4.58
	(0.30)		(0.46)
Cold	8.78	pH×1[pH<Min. pH]	0.52
	(0.38)		(0.28)
Cold×Season	-78.33	pH×1[pH>Max. pH]	-0.65
	(3.37)		(0.35)
Cold×Saturated Fat%	-22.61	Water Erosion	0.57
	(1.80)		(0.22)
Heat	-1.35	Water Erosion×Roots	-3.06
	(0.24)		(0.34)
Heat×RUE	2.16	Water Erosion×Height	2.59
	(0.37)		(0.41)
Heat×Saturated Fat%	0.30	Slope	-5.40
	(0.27)		(0.42)
Sunshine	1.32	Slope×Roots	14.06
	(0.25)		(0.81)
Sunshine×1[Long-Day Crop]	1.81	Slope×Height	-20.58
	(0.11)		(1.23)
Sunshine×RUE	-5.25	Constant	-5,835.42
	(0.35)		(244.51)
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy and county dummy to capture the cross-sectional unobserved effects). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.6 Yield Reduction Parameter (λ)

Panel A: Rainfall Deficiency		Panel B: Rainfall Surplus		Panel C: Temperature Deficiency		Panel D: Temperature Surplus	
Flaxseed	-13.11	Peanuts	-9.68	Cotton	-71.70	Beans	-1.34
Sugarbeets	-12.91	Lentils	-8.74	Sugarcane	-69.55	Soybeans	-0.92
Oats	-10.57	Sugarbeets	-8.36	Peanuts	-64.68	Alfalfa	-0.87
Rapeseed	-10.40	Alfalfa	-8.36	Soybeans	-17.25	Lentils	-0.80
Rye	-9.94	Flaxseed	-7.24	Safflower	-14.40	Rice	-0.45
Safflower	-9.24	Safflower	-6.48	Lentils	-13.79	Peanuts	-0.41
Peas	-9.15	Mustard	-6.48	Rapeseed	-9.45	Rapeseed	-0.31
Sunflower	-9.01	Soybeans	-6.48	Flaxseed	-8.84	Oats	-0.23
Mustard	-8.43	Rapeseed	-4.61	Sunflower	-5.96	Peas	-0.19
Soybeans	-8.40	Oats	-3.46	Mustard	-3.69	Cotton	-0.17
Lentils	-8.24	Potatoes	-3.46	Beans	-3.33	Tobacco	-0.17
Beans	-7.83	Barley	-2.52	Rice	-2.68	Safflower	-0.13
Barley	-6.54	Peas	-1.58	Sugarbeets	-2.30	Barley	-0.01
Corn	-6.28	Beans	-1.58	Tobacco	-2.21	Potatoes	0.05
Peanuts	-5.96	Wheat	-1.02	Rye	-0.12	Wheat	0.07
Cotton	-5.83	Cotton	-0.85	Potatoes	0.27	Sugarcane	0.22
Wheat	-5.10	Tobacco	-0.85	Wheat	1.63	Sorghum	0.24
Alfalfa	-4.15	Rice	-0.83	Oats	2.06	Flaxseed	0.30
Sorghum	-3.89	Rye	-0.65	Peas	3.38	Sugarbeets	0.47
Rice	-3.19	Sorghum	0.29	Barley	4.44	Mustard	0.51
Tobacco	-2.00	Sunflower	4.79	Sorghum	4.52	Sunflower	0.58
Sugarcane	0.67	Corn	7.81	Corn	4.96	Corn	0.66
Potatoes	1.85	Sugarcane	15.33	Alfalfa	5.32	Rye	0.82

Note: Table presents the marginal effects of rainfall deficiency, rainfall surplus, temperature deficiency, and temperature surplus on crop yield in percentage points for the twenty-three field crops widely grown in the contiguous U.S. counties.

As can be seen from Table 1.5, a one cm increase in *rainfall surplus* (increase in flood) decreases crop yield by 9.68% for the most flood-intolerant crop but decreases yield less for other crops, depending on their height and root types—fibrous or taproot. The crop yield reduction parameters by flood are ranked and presented in Panel B in Table 1.6. The five most flood-intolerant crops are peanuts, lentils, sugarbeets, alfalfa, and flaxseed, while the five most flood tolerant crops are sugarcane, corn, sunflower, sorghum, and rye. Peanuts and sugarbeets are typical taproot crops. Excess rainfall rots the root and decreases yield. However, since the pre-defined *rainfall surplus* is within the optimal water range for sugarcane, corn, and sunflower, excess rainfall is beneficial for these crops.

As can be seen from Table 1.5, a one degree Celsius increase in *temperature deficiency* increases crop yield by 8.78% for the crop that is most tolerant of temperature deficiency but decreases crop yields for most crops, depending on their growing season length and saturated fat content. The crop yield reduction parameters by temperature deficiency are ranked and presented in Panel C in Table 1.6. The five most cold-intolerant crops are cotton, sugarcane, peanuts, soybeans, and safflower, while the five most cold-tolerant crops are alfalfa, corn, sorghum, barley, and peas. Note that since there is nothing like irrigation to mitigate the impacts of cold, these rankings are all as expected.

As can be seen from Table 1.5, a one degree Celsius increase in *temperature surplus* decreases crop yield by 1.35% for the most heat intolerant crop but decreases yield less for other crops, depending on their RUE and saturated fat content. The crop yield reduction parameters for temperature surplus are ranked and presented in Panel D in Table 1.6. The five most heat-intolerant crops are beans, soybeans, alfalfa, lentils, and peanuts, while the five most heat-tolerant crops are rye, corn, sunflower, mustard, and sugarbeets.

B. Adaptation to Soil

Soil moisture is the most influential factor in determining crop yields and farmland value. A one percent decrease in soil moisture decreases crop yield by 42.42% for the most drought-intolerant crops but decreases yield less for other crops, depending on their WUE, root depth, and stomata density. In places where soil moisture is lacking, growing crops with high WUE, long root, and high stomata density help reduce water use or extract water from underground.

Soil pH around 5.5 is generally optimal for crop growth. However, when soil pH is below the crop's minimum tolerant pH level, crop yield on average is decreased by 0.52%; when soil pH is above the crop's maximum tolerant pH level, crop yield on average is decreased by 0.65%.

Soil water erosion[13] has a positive effect on crop yields, possibly because soil water erosion is correlated with omitted variable such as irrigation which is positively correlated with soil water erosion and has a positive effect on crop yields. Therefore, root depth is less valuable on soil that is accessible to irrigation.

Soil slope hurts crop yield, possibly because slope makes it difficult for planting and harvesting by large machines. There is a positive interaction between soil slope and root depth, possibly because long roots help prevent soil erosion.

IV. Out-of-Sample Prediction

To test the out-of-sample performance of the model, I omit each year in the sample and use the remaining years to predict farmland value in the omitted year. Figure 1.7 plots the actual

[13] Hornbeck (2012) studies the impacts of wind erosion on farmland value and farm revenue and finds that the American Dust Bowl in the 1930s has enduring impacts on current farmland values in high-eroded counties.

county-level farmland values versus the out-of-sample predicted county-level farmland values. The vertical axis is the actual farmland value while the horizontal axis is the predicted farmland value, labeled by $1,000. The solid lines are the 45 degree lines associated with a perfect fit, while the dashed lines are the real fitted lines. In general, the model performs well in out-of-sample prediction when crop prices are within the historical range, but generates substantial bias when crop prices are out of the historical range. For example, crop prices are extremely low in 1987. Thus, omitting 1987 data in estimation and predicting land values for 1978 will result in an out-of-range prediction. Likewise, crop prices are extremely high in 2007. Thus, omitting 2007 data in estimation and predicting land values for 2007 will result in an out-of-range prediction. In fact, predicted farmland value is higher than actual farmland value in 1987, while predicted farmland value is lower than actual farmland value in 2007. Nevertheless, since crop prices are explicit in the model, I can perform sensitivity analysis of crop prices on farmland value, even though crop prices are assumed to be exogenous in the model.

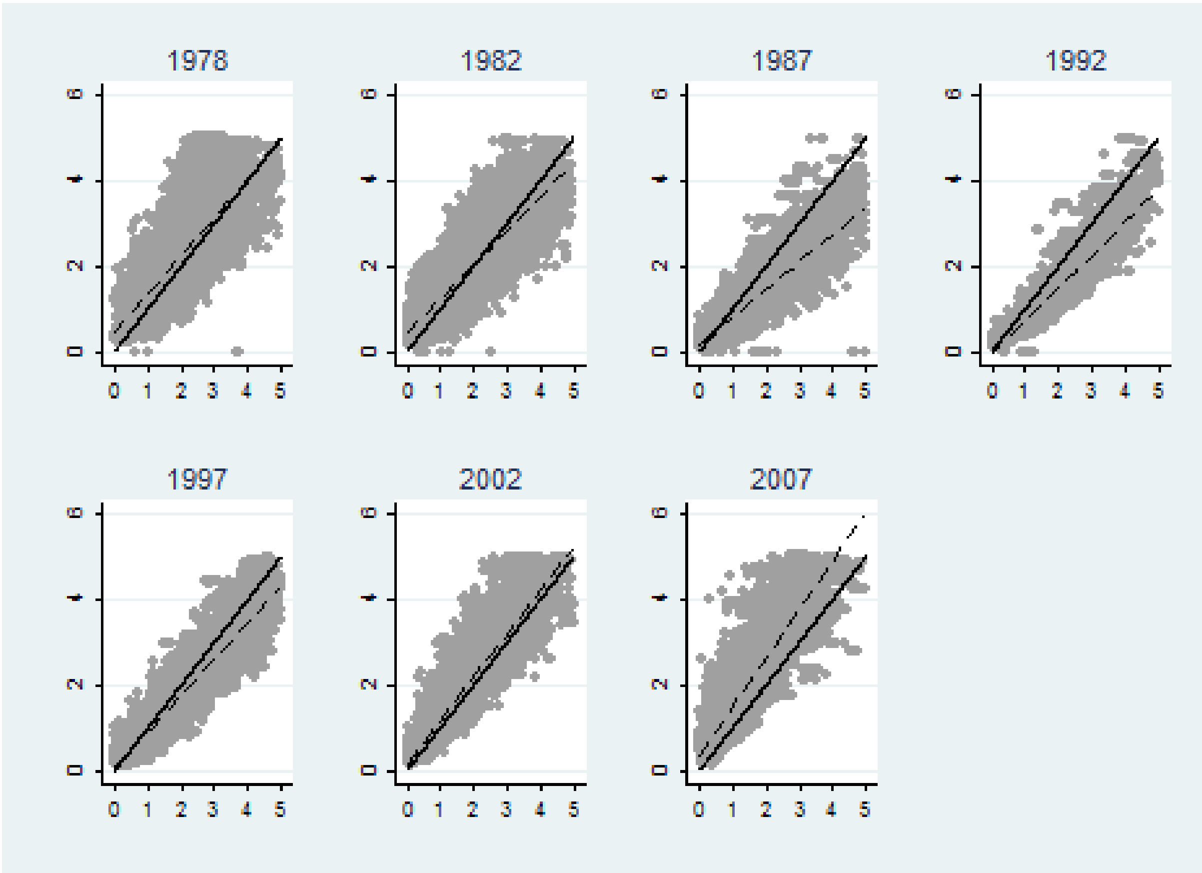


Figure 1.7 Out-of-Sample Predictions of Farmland Value

Note: Figure plots the actual county-level farmland values versus the out-of-sample predicted county-level farmland values, labeled by each $1,000. The vertical axis is the actual farmland value and the horizontal axis is the predicted farmland value. The solid lines are the 45 degree lines which assume perfect fit, while the dashed lines show the fitted values from a regression of actual on predicted values (i.e., the fitted values associated with the scatter plot).

IV. Robustness Checks

A. Irrigation

Applied economists tend to use Eastern U.S. counties to study the effect of drought on crop yields and on farmland value because, as they argue, unobserved irrigation will bias the coefficient on drought (Schlenker, Hanemann, and Fisher 2005, 2006). Table 1.7 presents regression results using Eastern U.S. counties. In general, the coefficients on rainfall deficiency, temperature surplus, and soil moisture are larger, while the coefficient on land-use choice is smaller than when I use all U.S. counties. Table 1.8 presents crop yield reduction parameters by climate extremes. Crops are more sensitive to drought and heat in the Eastern United States. However, the rankings are mostly consistent with the model using all U.S. counties, except for rice under rainfall deficiency conditions. In the East, rice exhibits extreme sensitivity to drought, while sugarcane and potatoes remain at the bottom of the ranking. One possible explanation is that rice is grown in both the East and West. Rice growers in the East do not irrigate significantly, while rice growers in the West irrigate significantly. The difference in the yield reduction parameters between the full U.S. sample and the Eastern U.S. sample implies that irrigation may have allowed rice to recoup up to 14% of yield losses due to drought. An alternative explanation is not about irrigation but about crop varieties. In the East, farmers grow long-grain rice, which has higher yields. In the West, farmers grow short or medium-grain rice, which have lower yields but better flavor. Thus, one hypothesis is that the difference in rice yields between the East and the West is purely due to difference in varieties. As to sugarcane, it is always irrigated and grown in the Eastern United States, so using the Eastern U.S. sample does not help to recover the response of sugarcane to drought conditions. In sum, using the Eastern U.S. sample may help to mitigate bias related to omitted irrigation.

Table 1.7 Determinants of Agricultural Land Value (U.S. East)

Variables	I	Variables	II
Log Crop Share	-896.40		
	(28.43)		
Drought	-23.37	Moisture	53.45
	(1.27)		(2.34)
Drought×WUE	14.64	Moisture Squared	-0.08
	(0.83)		(0.05)
Drought×Roots	15.21	Moisture×WUE	-36.51
	(0.85)		(1.22)
Drought×Stomata	-3.13	Moisture×Roots	-31.52
	(2.25)		(1.25)
Flood	-3.74	Moisture×Stomata	-5.90
	(0.24)		(2.99)
Flood×Height	7.96	pH	65.69
	(0.52)		(4.64)
Flood×Fibrous Root	2.65	pH Squared	-5.58
	(0.21)		(0.41)
Cold	6.53	pH×1[pH<Min. pH]	0.54
	(0.27)		(0.19)
Cold×Season	-58.75	pH×1[pH>Max. pH]	0.00
	(2.41)		(0.25)
Cold×Saturated Fat%	-10.65	Water Erosion	-0.22
	(1.16)		(0.16)
Heat	-2.89	Water Erosion×Roots	-1.69
	(0.27)		(0.23)
Heat×RUE	4.57	Water Erosion×Height	1.57
	(0.42)		(0.28)
Heat×Saturated Fat%	1.41	Slope	-3.76
	(0.21)		(0.29)
Sunshine	-1.66	Slope×Roots	8.98
	(0.20)		(0.54)
Sunshine×1[Long-Day Crop]	1.58	Slope×Height	-13.31
	(0.08)		(0.83)
Sunshine×RUE	-1.91	Constant	-3,280.82
	(0.24)		(146.57)
Observations	104,333		
Number of Counties	2,593		
Crop Fixed Effect	Y		
County Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted log (crop share) from first-stage regression; and (4) controls (crop dummy and county dummy to capture the cross-sectional unobserved effects) using U.S. East counties. All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.8 Yield Reduction Parameter (λ) (U.S. East)

Panel A: Rainfall Deficiency		Panel B: Rainfall Surplus		Panel C: Temperature Deficiency		Panel D: Temperature Surplus	
Flaxseed	-22.16	Peanuts	-3.74	Cotton	-53.23	Beans	-2.82
Sugarbeets	-21.90	Lentils	-3.37	Sugarcane	-52.22	Alfalfa	-1.85
Rapeseed	-19.58	Sugarbeets	-3.22	Peanuts	-42.26	Lentils	-1.71
Rye	-17.33	Alfalfa	-3.22	Soybeans	-10.33	Soybeans	-1.65
Lentils	-17.13	Flaxseed	-2.77	Lentils	-10.24	Rice	-0.97
Peas	-17.09	Safflower	-2.48	Safflower	-7.45	Rapeseed	-0.54
Oats	-16.83	Soybeans	-2.48	Rapeseed	-5.89	Oats	-0.39
Rice	-16.77	Mustard	-2.48	Flaxseed	-3.30	Tobacco	-0.39
Sunflower	-16.17	Rapeseed	-1.73	Mustard	-2.79	Peas	-0.38
Safflower	-15.99	Oats	-0.57	Beans	-2.24	Cotton	-0.33
Beans	-15.59	Potatoes	-0.57	Rice	-1.93	Peanuts	-0.12
Soybeans	-15.08	Cotton	-0.24	Sugarbeets	-1.76	Barley	-0.01
Mustard	-15.05	Tobacco	-0.24	Tobacco	-1.72	Potatoes	0.09
Corn	-12.52	Barley	-0.20	Sunflower	-0.41	Safflower	0.12
Barley	-11.89	Peas	0.17	Rye	0.04	Wheat	0.18
Cotton	-9.99	Beans	0.17	Potatoes	0.22	Sugarcane	0.43
Peanuts	-8.99	Wheat	0.40	Wheat	1.63	Sorghum	0.52
Sorghum	-8.94	Rice	0.47	Oats	2.60	Sugarbeets	0.97
Wheat	-7.32	Rye	0.55	Peas	2.84	Flaxseed	1.01
Alfalfa	-5.83	Sorghum	0.92	Barley	3.72	Mustard	1.04
Tobacco	-2.69	Sunflower	1.99	Sorghum	3.76	Corn	1.39
Potatoes	-2.24	Corn	3.89	Corn	3.96	Sunflower	1.71
Sugarcane	0.46	Sugarcane	6.87	Alfalfa	4.13	Rye	1.72

Note: Table presents the marginal effects of rainfall deficiency, rainfall surplus, temperature deficiency, and temperature surplus on crop yield in percentage points for the twenty-three field crops widely grown in the contiguous U.S. East counties.

Table 1.9 Determinants of Agricultural Land Value (Crop × Region)

Variables	I	Variables	II
Log Crop Share	-1,679.69		
	(51.60)		
Drought	-6.53	Moisture	20.92
	(1.24)		(2.83)
Drought×WUE	6.54	Moisture Squared	0.43
	(0.78)		(0.07)
Drought×Roots	2.44	Moisture×WUE	-24.26
	(0.91)		(1.25)
Drought×Stomata	2.21	Moisture×Roots	-19.94
	(2.43)		(1.39)
Flood	-6.42	Moisture×Stomata	-18.71
	(0.38)		(3.68)
Flood×Height	10.45	pH	48.33
	(0.83)		(5.95)
Flood×Fibrous Root	4.71	pH Squared	-3.68
	(0.33)		(0.51)
Cold	8.48	pH×1[pH<Min. pH]	1.06
	(0.43)		(0.29)
Cold×Season	-67.43	pH×1[pH>Max. pH]	0.05
	(3.65)		(0.37)
Cold×Saturated Fat%	-29.68	Water Erosion	-0.78
	(2.27)		(0.24)
Heat	1.64	Water Erosion×Roots	1.26
	(0.27)		(0.38)
Heat×RUE	-2.61	Water Erosion×Height	1.45
	(0.42)		(0.47)
Heat×Saturated Fat%	-0.34	Slope	-5.67
	(0.37)		(0.45)
Sunshine	0.45	Slope×Roots	14.97
	(0.28)		(0.86)
Sunshine×1[Long-Day Crop]	1.32	Slope×Height	-26.22
	(0.12)		(1.38)
Sunshine×RUE	-2.73	Constant	
	(0.35)		
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		
Crop × Region Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy, county dummy, and crop × region dummy to capture the cross-sectional unobserved effects). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.10 Determinants of Agricultural Land Value (Crop × Region, Year Dummy)

Variables	I	Variables	II
Log Crop Share	-1,604.48		
	(107.47)		
Drought	-10.33	Moisture	10.56
	(1.24)		(2.71)
Drought×WUE	9.48	Moisture Squared	0.41
	(0.86)		(0.07)
Drought×Roots	4.19	Moisture×WUE	-16.60
	(0.87)		(1.33)
Drought×Stomata	5.98	Moisture×Roots	-13.47
	(2.33)		(1.38)
Flood	-4.90	Moisture×Stomata	-14.19
	(0.45)		(3.55)
Flood×Height	7.03	pH	32.10
	(0.86)		(6.05)
Flood×Fibrous Root	3.10	pH Squared	-2.51
	(0.35)		(0.53)
Cold	6.11	pH×1[pH<Min. pH]	0.56
	(0.57)		(0.28)
Cold×Season	-44.87	pH×1[pH>Max. pH]	0.10
	(4.57)		(0.36)
Cold×Saturated Fat%	-35.26	Water Erosion	-0.95
	(2.94)		(0.24)
Heat	1.35	Water Erosion×Roots	1.52
	(0.28)		(0.38)
Heat×RUE	-2.29	Water Erosion×Height	1.17
	(0.43)		(0.45)
Heat×Saturated Fat%	0.22	Slope	-5.66
	(0.35)		(0.53)
Sunshine	0.55	Slope×Roots	14.68
	(0.27)		(1.15)
Sunshine×1[Long-Day Crop]	0.02	Slope×Height	-25.54
	(0.12)		(1.92)
Sunshine×RUE	-1.23	Constant	-4,711.99
	(0.34)		(484.91)
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		
Crop × Region Fixed Effect	Y		
Year Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy, county dummy, and crop × region dummy to capture the cross-sectional unobserved effects and year dummy to capture the aggregate effects over time). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.11 Determinants of Agricultural Land Value (Crop × Region, Socioeconomic Factors)

Variables	I	Variables	II
Log Crop Share	-1,491.99		
	(106.37)		
Drought	-9.43	Moisture	9.67
	(1.17)		(2.53)
Drought×WUE	8.88	Moisture Squared	0.38
	(0.82)		(0.07)
Drought×Roots	3.65	Moisture×WUE	-15.10
	(0.82)		(1.27)
Drought×Stomata	5.69	Moisture×Roots	-12.35
	(2.17)		(1.30)
Flood	-4.64	Moisture×Stomata	-13.89
	(0.43)		(3.32)
Flood×Height	6.91	pH	31.41
	(0.81)		(5.70)
Flood×Fibrous Root	2.91	pH Squared	-2.48
	(0.33)		(0.50)
Cold	5.18	pH×1[pH<Min. pH]	0.53
	(0.55)		(0.26)
Cold×Season	-37.39	pH×1[pH>Max. pH]	0.08
	(4.42)		(0.33)
Cold×Saturated Fat%	-35.47	Water Erosion	-0.98
	(2.81)		(0.23)
Heat	1.20	Water Erosion×Roots	1.47
	(0.26)		(0.36)
Heat×RUE	-2.06	Water Erosion×Height	1.23
	(0.40)		(0.42)
Heat×Saturated Fat%	0.21	Slope	-5.31
	(0.33)		(0.51)
Sunshine	0.52	Slope×Roots	13.66
	(0.25)		(1.13)
Sunshine×1[Long-Day Crop]	0.02	Slope×Height	-23.96
	(0.11)		(1.90)
Sunshine×RUE	-1.29	Constant	-5,432.60
	(0.32)		(478.57)
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		
Crop × Region Fixed Effect	Y		
Socioeconomic Variables	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy, county dummy, and crop × region dummy to capture the cross-sectional unobserved effects and socioeconomic factors which may be correlated with climate variables and also have impacts on farmland value). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.12 Determinants of Agricultural Land Value (Crop × Region, Crop × Year)

Variables	I	Variables	II
Log Crop Share	-867.46		
	(48.33)		
Drought	-5.57	Moisture	10.65
	(1.09)		(1.87)
Drought×WUE	2.78	Moisture Squared	0.39
	(0.66)		(0.05)
Drought×Roots	4.73	Moisture ×WUE	-15.61
	(0.80)		(0.90)
Drought×Stomata	2.14	Moisture ×Roots	-12.09
	(1.98)		(0.93)
Flood	-2.31	Moisture ×Stomata	-13.84
	(0.24)		(3.36)
Flood×Height	2.95	pH	-38.80
	(0.52)		(6.80)
Flood×Fibrous Root	1.20	pH Squared	3.39
	(0.20)		(0.55)
Cold	3.19	pH×1[pH<Min. pH]	0.07
	(0.29)		(0.17)
Cold ×Season	-24.56	pH×1[pH>Max. pH]	-0.72
	(2.44)		(0.21)
Cold ×Saturated Fat%	-26.27	Water Erosion	-0.82
	(1.91)		(0.14)
Heat	0.02	Water Erosion×Roots	1.68
	(0.15)		(0.24)
Heat ×RUE	-0.05	Water Erosion×Height	-0.94
	(0.24)		(0.31)
Heat ×Saturated Fat%	0.57	Slope	-4.08
	(0.22)		(0.31)
Sunshine	3.99	Slope×Roots	10.01
	(0.53)		(0.67)
Sunshine×1[Long-Day Crop]	0.74	Slope×Height	-16.35
	(0.22)		(1.06)
Sunshine×RUE	-7.67	Constant	-2,199.29
	(0.82)		(437.97)
Observations	116,691		
Number of Counties	2,990		
Crop Fixed Effect	Y		
County Fixed Effect	Y		
Crop × Region Fixed Effect	Y		
Crop × Year Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland value on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy, county dummy, and crop × region dummy to capture the cross-sectional unobserved effects and crop × year dummy to control for crop subsidies which are correlated with crop revenue and also have impacts on farmland value). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read.

Table 1.13 Determinants of Agricultural Land Value (Rent)

Variables	I	Variables	II
Log Crop Share	-62.52		
	(4.29)		
Drought	-1.14	Moisture	2.50
	(0.14)		(0.26)
Drought×WUE	0.85	Moisture Squared	-0.01
	(0.09)		(0.01)
Drought×Roots	0.62	Moisture×WUE	-1.68
	(0.09)		(0.14)
Drought×Stomata	0.53	Moisture×Roots	-1.29
	(0.19)		(0.13)
Flood	-0.46	Moisture×Stomata	-1.57
	(0.04)		(0.28)
Flood×Height	1.03	pH	2.23
	(0.09)		(0.47)
Flood×Fibrous Root	0.24	pH Squared	-0.25
	(0.03)		(0.04)
Cold	0.42	pH×1[pH<Min. pH]	-0.02
	(0.04)		(0.02)
Cold×Season	-3.46	pH×1[pH>Max. pH]	0.05
	(0.31)		(0.03)
Cold×Saturated Fat%	-0.20	Water Erosion	0.04
	(0.15)		(0.02)
Heat	-0.09	Water Erosion×Roots	-0.16
	(0.02)		(0.03)
Heat×RUE	0.12	Water Erosion×Height	0.16
	(0.03)		(0.04)
Heat×Saturated Fat%	-0.22	Slope	-0.33
	(0.04)		(0.04)
Sunshine	-0.03	Slope×Roots	0.91
	(0.03)		(0.09)
Sunshine×1[Long-Day Crop]	0.07	Slope×Height	-1.36
	(0.01)		(0.13)
Sunshine×RUE	-0.03	Constant	
	(0.04)		
Observations	48,196		
Number of Counties	2,883		
Crop Fixed Effect	Y		
County Fixed Effect	Y		

Note: Table shows the 2SLS regression results of farmland rent on (1) the interactions between crop maximum revenue and soil and climate characteristics, (2) the interactions between crop maximum revenue, soil and climate characteristics, and crop attributes, (3) predicted ln(crop share) from first-stage regression; and (4) controls (crop dummy, county dummy, and crop × region dummy to capture the cross-sectional unobserved effects). All variables in the table (except log (crop share) and the constant) include interactions with crop maximum revenue. I suppress this interaction in the variable labels to make the table easier to read. Rent data are from Census of Agriculture 1997, 2002, and 2007.

B. Zero Shares

One concern with dropping zero shares is that this will cause bias, because zero shares do not occur randomly but, indeed, are likely due to locally poor conditions for growing a crop. However, zeros are clustered geographically. Thus, I attempt to mitigate potential bias associated with zero shares by including crop × region dummies, so that I only use within-region variation in relative crop shares and land values for identification. Table 1.9 presents the regression results of adding crop × region dummy variables. Generally, the regression results are consistent with the main regression, suggesting that discarding observations with log zeros may not be unrealistic in this paper's setting. However, smaller coefficients on drought-related variables are observed when I control for the crop × region unobserved effects. Alternative approaches to deal with log zeros include adding arbitrarily small numbers prior to taking logs (Timmins 2006), fitting multinomial logit models separately for each pre-defined choice sets or modeling multinomial logit models with varying choice set (Yamamoto 2014), modeling the choice set and land-use choice in two stages (Ben-Akiva and Boccava 1995), and imputing missing data using Markov Chain Monte Carlo simulation (MCMC) (Katz and King 1999). I plan to apply MCMC to impute the missing log zero shares data in a future draft.

C. Other Specifications

I also test the model specification by including the following controls, in addition to crop × region dummies: year dummies to control for aggregate effects that are common to all crops in all counties in a single year, crop × year dummies to control for differential trends by crop (e.g., subsidies or technologies) that vary by crop and year, and socioeconomic variables such as population density and per-capita income, which may affect farmland value and are also correlated with climate variables. Tables 1.10-1.12 present the regression results for these other specifications. In general, coefficients are consistent across different specifications, but I observe smaller coefficients when adding crop × year dummies.

D. Cash Rent

Since land rental rate is the main determinant of farmland value, I want to test how the land rental rate is affected by climate extremes and soil variables. Table 1.13 shows the regression results using cash rent as the dependent variable. On average, if I assume a 5%[14] real interest rate, the results of using cash rent as the dependent variable are consistent with those using farmland value as the dependent variable.

E. Base Category

All above analyses focus on how climate extremes and soil characteristics affect the yield of field crops, which account for one third of U.S. farmland. The remaining two thirds of farmland is in pasture, which I treat as the base land-use category in my analysis. I do not model this land explicitly, as my inclusion of county dummies implicitly controls for the base category, such that the econometric results above are unaffected. However, when modeling impacts of climate change on overall farmland values, we may care about pasture, which accounts for such a large share of

[14] Mendelsohn, Nordhaus, and Shaw (1994) used a 5% discount rate.

farmland. Since there is no county-level panel data on pasture prices and attributes, I cannot estimate the yield response function of pasture together with the field crops. Gould (2013) finds, however, that the value of pastureland depends largely on cattle prices and corn prices over time. Therefore, I fit a pasture value function as the following:

(18) $$V_{pct} = p_{cattle,t} \boldsymbol{z}_{ct}^{'} \boldsymbol{\alpha_{cattle}},$$

where V_p is the per acre pastureland value, p_{cattle} is the cattle price ($ per cwt), and $\boldsymbol{z}_{ct}$ is soil and climate characteristics. I run the above regression to estimate $\boldsymbol{\alpha_{cattle}}$, which is the coefficient vector with units cwt per acre.

Given my structural model, the formula to construct the dependent variable for this regression is given by:

(19) $$V_{pct} = E(U_{ct}) + \hat{\sigma} \ln(s_{pct}),$$

where $E(U_{ct})$ is the average farmland value, $\hat{\sigma}$ is the estimated scale parameter obtained from the main regression on field crops, and s_{pct} is the land share devoted to pasture.

Table 1.14 Pasture Value

Variable	I	II	III	IV
Drought	-1.272	-0.379	-0.411	0.491
	(0.128)	(0.122)	(0.302)	(0.298)
Flood	0.383	0.371	0.037	0.015
	(0.066)	(0.062)	(0.133)	(0.130)
Cold	-0.344	-0.372	-0.418	-0.510
	(0.028)	(0.027)	(0.078)	(0.076)
Heat	-0.093	-0.107	-0.013	-0.090
	(0.023)	(0.022)	(0.062)	(0.060)
Sunshine	-0.710	-1.006	-1.040	-1.130
	(0.073)	(0.069)	(0.184)	(0.178)
Moisture	-7.937	-7.401	-5.877	-7.192
	(0.960)	(0.901)	(1.995)	(1.940)
Moisture Squared	0.312	0.293	0.252	0.291
	(0.032)	(0.030)	(0.066)	(0.064)
pH	29.945	34.537	28.575	34.890
	(2.325)	(2.183)	(5.166)	(5.038)
pH Squared	-1.552	-2.058	-1.747	-2.370
	(0.183)	(0.172)	(0.416)	(0.406)
Water Erosion	0.243	0.066	0.259	0.012
	(0.058)	(0.055)	(0.118)	(0.116)
Slope	-1.107	-1.366	-1.156	-1.306
	(0.107)	(0.101)	(0.241)	(0.238)
Per Capita Income		6.111		7.816
		(0.214)		(0.457)
Population Density		7.317		4.253
		(0.338)		(0.449)
Population Density Squared		-0.002		-0.000
		(0.000)		(0.000)
Constant	33.917	-2,746.734	744.544	-2,398.849
	(36.797)	(72.264)	(74.350)	(155.314)
Observations	17,138	16,998	18,120	17,948
R-squared	0.150	0.256	0.024	0.058
Number of Counties	2,855	2,832	2,605	2,581

Note: Table shows the regression results of pasture land value on climate extremes and soil characteristics interacted with cattle prices. I suppress the cattle prices to make the table easy to read. Columns I and II use all U.S. counties. Columns III and IV use Eastern U.S. counties. Columns II and IV also include socioeconomic variables (population density and per capita income).

Table 1.14 presents the estimation of the pastureland value function. Column I use all U.S. counties, corresponding to the main regression for field crops. A once cm increase in drought decreases pasture productivity by 1.272 cattle cwt per acre. A one cm increase in flood increases pasture productivity by 0.383 cattle cwt per acre. A one Celsius degree increase in temperature deficiency decreases pasture productivity by 0.344 cattle cwt per acre. A one degree increase in temperature surplus decreases pasture productivity by 0.093 cattle cwt per acre. Columns II-IV use all U.S. counties with socioeconomic factors, Eastern U.S. counties without socioeconomic factors, and Eastern U.S. counties with socioeconomic factors as robustness checks. Estimates are robust across different specifications except that adding socioeconomic factors makes the negative effect of drought on pastureland less severe and the positive effect of flood on pastureland value less important.

V. Impacts of Climate Extremes on Farmland Value

A. Heterogeneous Marginal Impacts

To ease discussion, I will refer frequently to the nine USDA pre-defined farm resource regions. The nine regions include Basin and Range, Fruitful Rim, Northern Great Plains, Prairie Gateway, Heartland, Mississippi Portal, Northern Crescent, Eastern Uplands, and Southern Seaboard, as shown in Figure 8. Figures 1.9-1.12(a) show the marginal effects of climate extremes on cropland value when I allow land-use switching (defined as the business-as-usual adaptation strategy in this paper). The Mississippi area and the southern seaboard are the most vulnerable regions to rainfall deficiency, rainfall surplus, temperature deficiency, and temperature surplus. Counties in these regions may encounter a maximum reduction in average farmland value of -5.8%, -6.3%, -70%, and 0.3% under marginal increases in the aforementioned severe climate conditions. Rainfall deficiency and temperature surplus hurt everywhere else. Excess rainfall benefits the Heartland, by as much as 10.7% for an additional centimeter increase. Temperature deficiency benefits the Northern Great Plains, the Basin and Range, and the Northern Crescent, by as much as 2.6% for an additional degree Celsius decrease.

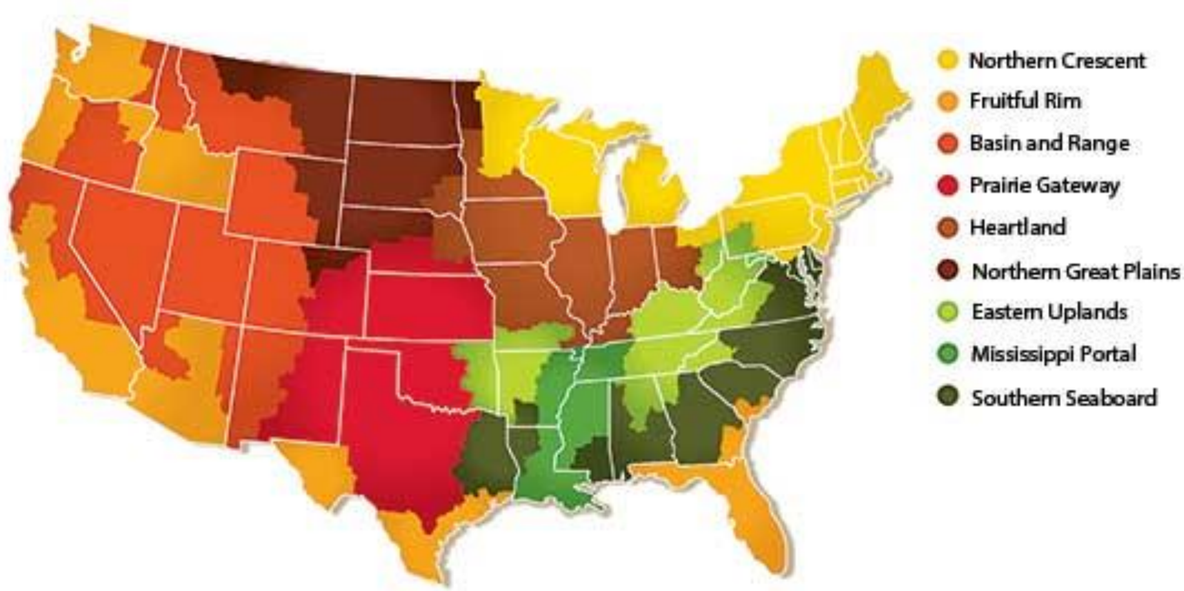
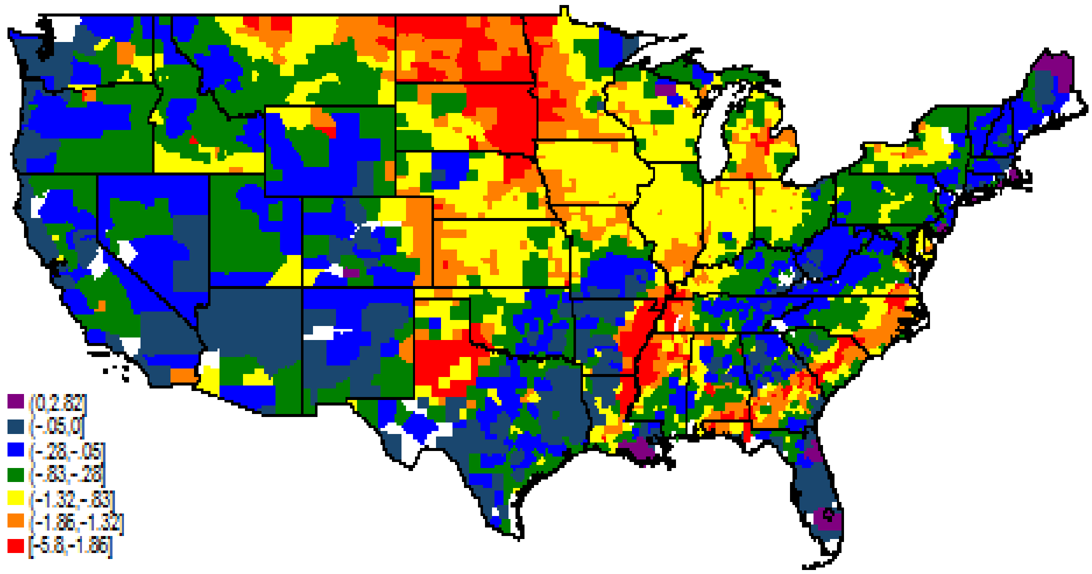
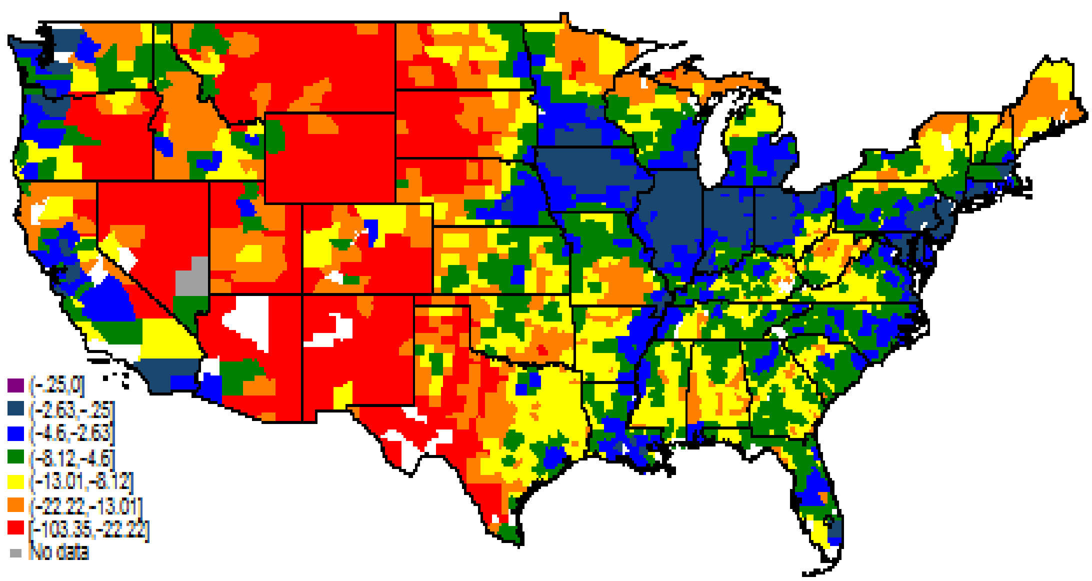


Figure 1.8 USDA Farm Resource Regions
Source: http://www.ers.usda.gov/publications/aib-agricultural-information-bulletin/aib760.aspx
Note: This figure shows the nine farm resource regions defined by the USDA Economic Research Services.



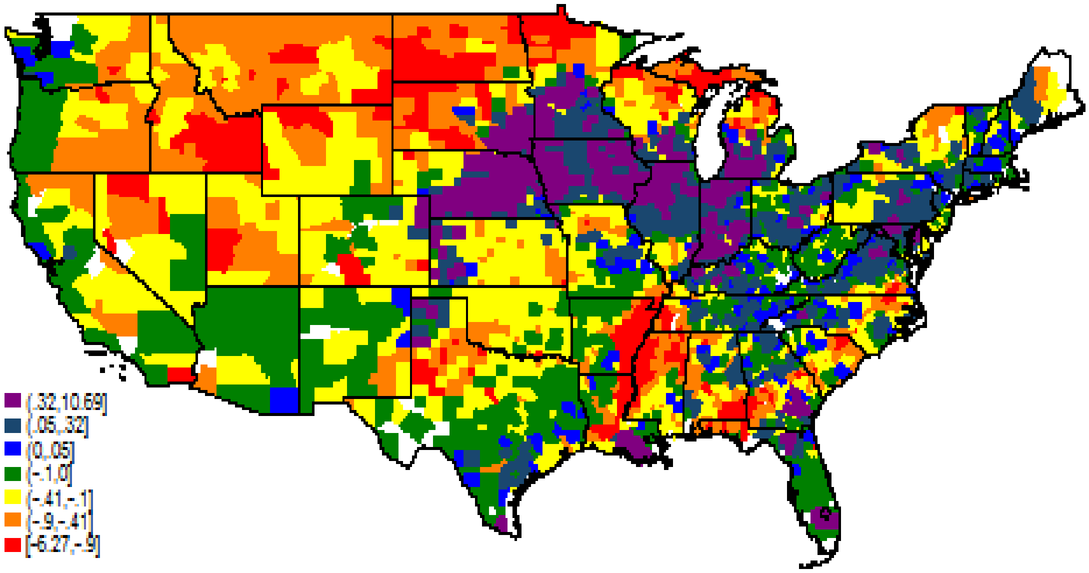
(a) Cropland



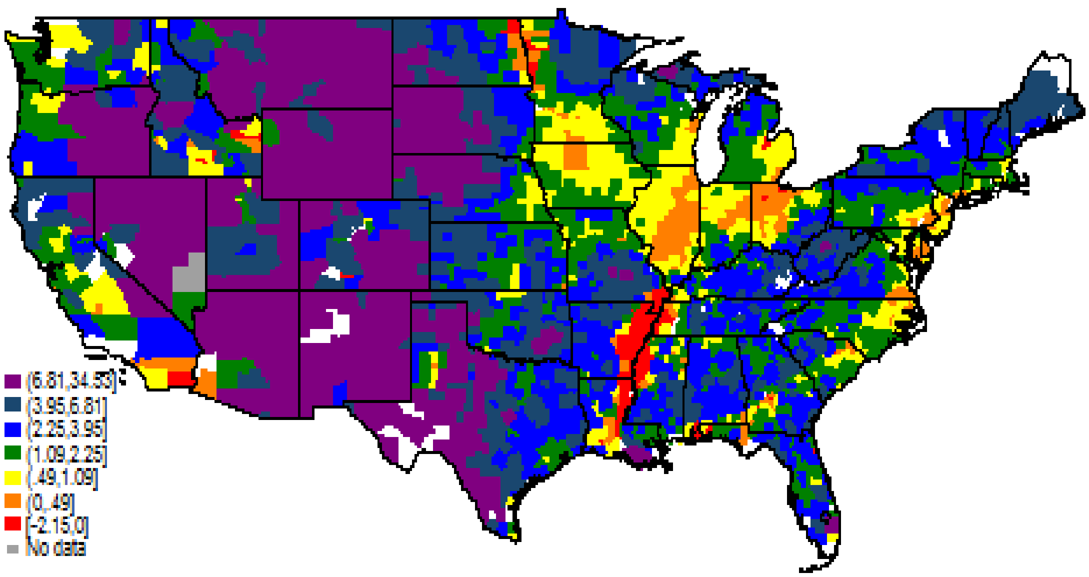
(b) Cropland + Pastureland

Figure 1.9 Marginal Effects of Rainfall Deficiency on Farmland Value in Percentage Points in 1978

Note: Map (a) shows the marginal effects of one centimeter decrease in rainfall under rainfall deficiency on cropland value (which accounts for 1/3 of farmland) in percentage points. Comparing across space, the Mississippi area, the southern seaboard, and part of the northern plains are hurt the most. In map (b), when I add pastureland (which accounts for 2/3 of farmland), the western pasture production regions are damaged the most.



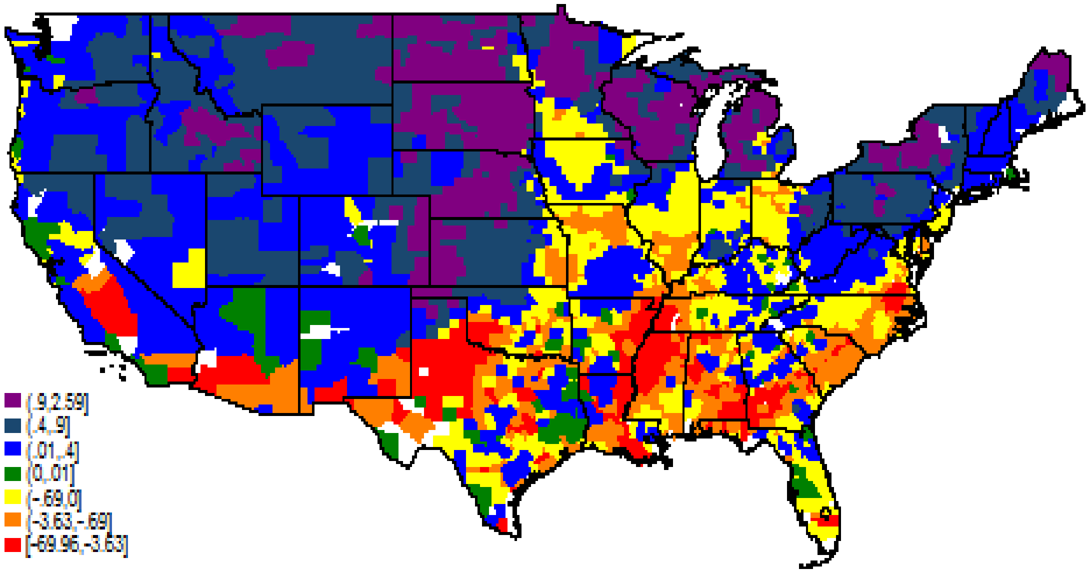
(a) Cropland



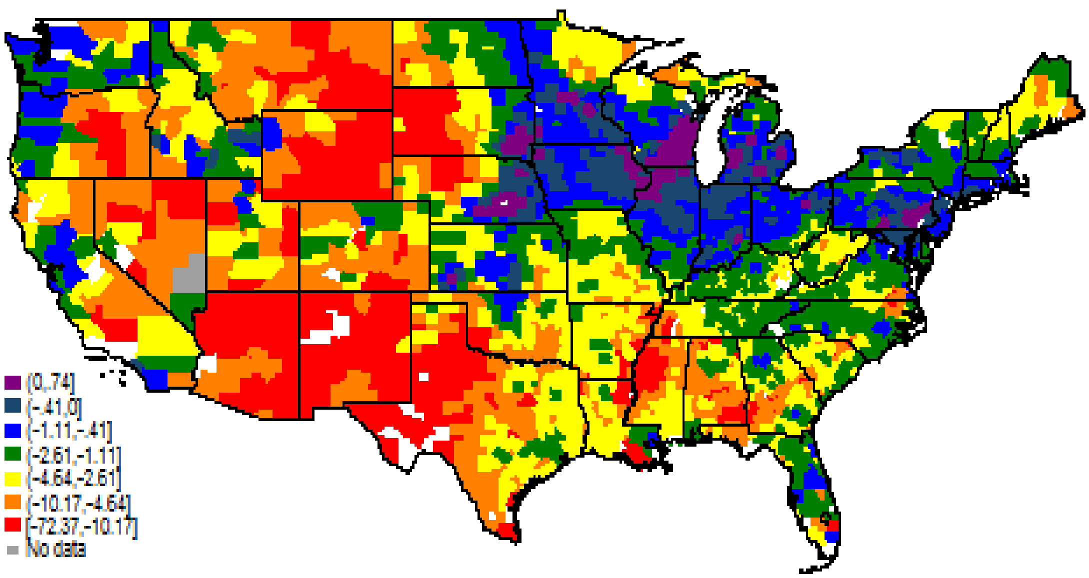
(b) Cropland + Pastureland

Figure 1.10 Marginal Effects of Rainfall Surplus on Farmland Value in Percentage Points in 1978

Note: Map (a) shows the marginal effects of one centimeter increase in rainfall under rainfall surplus on cropland value (which accounts for 1/3 of farmland) in percentage points. Comparing across space, the Mississippi area, the southern seaboard, and part of the northern plains are hurt the most. However, the corn belt gains from extra rainfall because corn is very water intensive. In map (b), when we add pastureland (which accounts for 2/3 of farmland), the western pasture production regions gain the most.



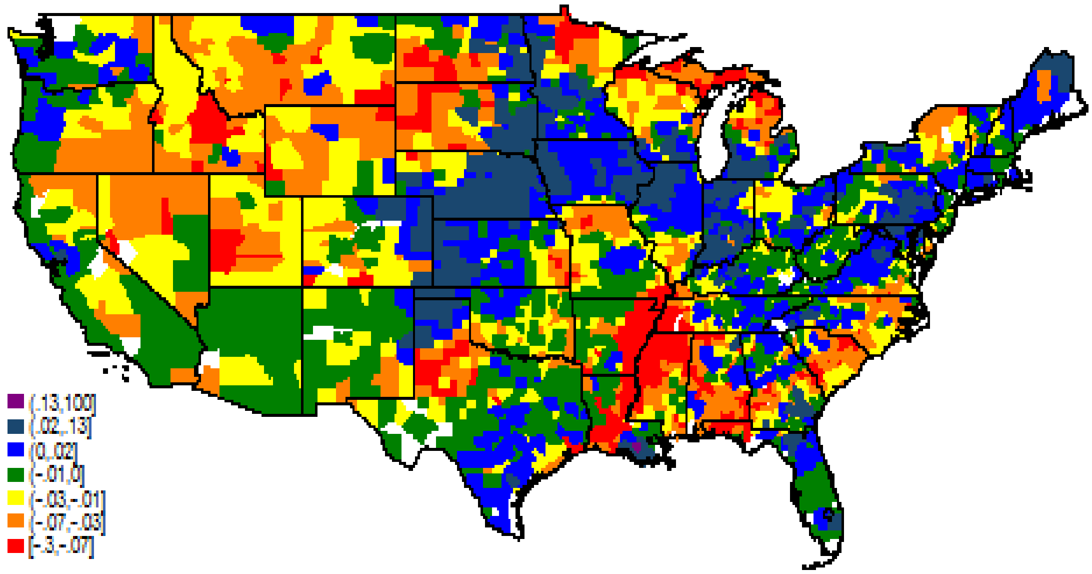
(a) Cropland



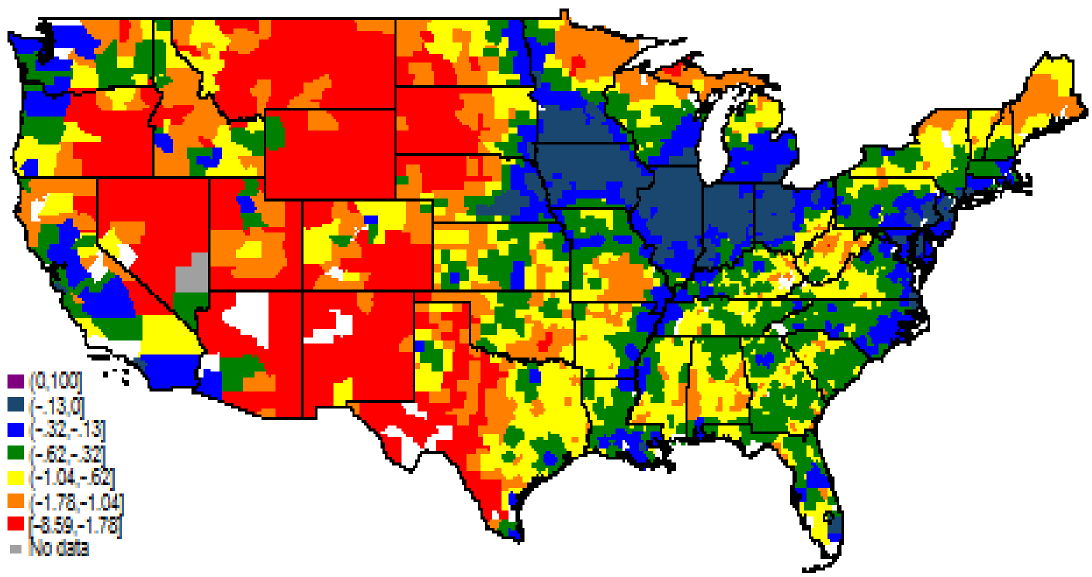
(b) Cropland + Pastureland

Figure 1.11 Marginal Effects of Cold on Farmland Value in Percentage Points in 1978

Note: Map (a) shows the marginal effects of one degree decrease in temperature under temperature deficiency on cropland value (which accounts for 1/3 of farmland) in percentage points. Comparing across space, the Mississippi area, the southern seaboard, and part of the Texas, Arizona, and California are hurt the most, while the wheat growing area gains. In map (b), when we add pastureland (which accounts for 2/3 of farmland), the western pasture production regions are damaged the most.



(a) Cropland



(b) Cropland + Pastureland

Figure 1.12 Marginal Effects of Temperature surplus on Farmland Value in Percentage Points in 1978

Note: Map (a) shows the marginal effects of one degree increase in temperature under temperature surplus on cropland value (which accounts for 1/3 of farmland) in percentage points. Comparing across space, the Mississippi area, the southern seaboard, and part of the northwest regions are hurt the most. In map (b), when we add pastureland (which accounts for 2/3 of farmland), the western pasture production regions are damaged the most.

Figures 1.9-1.12(b) show the marginal effects of climate extremes on farmland (cropland plus pastureland) value for the business-as-usual adaptation strategy. The Northern Great Plains, the Prairie Gateway, and the Basin & Range become the most vulnerable regions to drought, temperature deficiency, and temperature surplus due to the large influence of pastureland, with the maximum decrease in farmland value reaching -100%, -72.4%, and -8.6% for marginal increases in the severe climate conditions. The Mississippi Portal is the most vulnerable region to flood, decreasing by as much as 2.2% for an additional centimeter increase in rainfall surplus. Drought hurts everywhere else as well. Flood benefits the Northern Great Plains, the Prairie Gateway, and the Basin & Range, by as much as 34.6% with an additional centimeter increase. Temperature deficiency benefits a small number of counties in the Heartland, by up to 0.7% for an additional Celsius degree decrease.

B. Benefits from Selectively Changing Crop Attributes

To facilitate a comparison with the previous literature that uses econometrics to estimate the impacts of climate change on agriculture, this subsection estimates changes in farmland value under a uniform climate change scenario in which average temperature increases by 2.8°C (5°F) and average precipitation increases by 8% across all U.S. counties, which are consistent with a doubling of atmospheric CO_2. Although climate change will surely imply heterogeneous changes in climate across different regions, the assumption of homogeneous impacts is commonly used in this literature (Mendelsohn, Nordhaus, and Shaw 1994). I estimate these changes under four different assumptions for technological change to determine whether technology can mitigate the negative impacts or even augment the beneficial impacts of climate change.

The simulation procedures are as follows. First, obtain the coefficient estimates from the joint model of farmland value and crop choices. Second, construct future climate extremes—*rainfall deficiency, rainfall surplus, temperature deficiency, and temperature surplus* by adding 2.8°C (5°F) in temperature and 8% increase in precipitation to the daily temperature and precipitation in each day in 1950-2005 and. Third, apply the coefficients to the constructed future climate conditions to obtain future farmland value. Fourth, take the difference between the future farmland value and the current farmland value to obtain the change in farmland value.

Switch Land-Use. — This scenario represents the business-as-usual adaptation strategy in this paper. That is, neither new technology nor new crops are introduced. The crop choice set is not expanded, and land-use switching is limited to the local crop choice set. Since all crops have been grown in the county before, farmers already have the technology and have made the investments to grow these crops. Thus, land-use switching within the current set of chosen crops can be viewed as the most likely to happen in the near term. Overall, farmland value increases by 5% if farmers can freely switch to crops that have been grown locally in the past few decades. In contrast, the following three adaptation strategies involve technological change and yield higher benefits under the same climate change scenario.

Adopt Crops with Modified Attributes . — Agribusiness companies may invest in R&D in drought-tolerant and heat-tolerant crops. We have seen from the crop yield reduction table that soybeans are the most sensitive crop to drought and heat among the most widely grown field crops. Therefore, a super-soybean which is more drought and heat tolerant than the current varieties will likely yield large benefits. Farmers who adopt a super-soybean will expect less yield reduction in extreme drought and heat conditions and therefore will be less likely to shift to other crops. Overall, farmland value is increased by an additional 2.2% if farmer can adopt a super-soybean which has 30% higher stomata density15.

Apply Chemical Spray to a Group of Crops. — Similarly, agrichemical firms may invest in R&D in drought-tolerant and heat-tolerant chemicals. Overall, farmland value is increased by an additional 2.4% if such chemical can be sprayed to increase the stomata density of all the crops in farmer's choice set by 10%[16].

Adopt New Crops. — This will change the local crop choice set.

Let us take a hypothetical example. Cotton has never been grown in Ingham County, Michigan in the past three decades. After climate change, the location becomes more humid and hot, and fits cotton production. A new crop typically has a different set of attributes from the crops in the current choice set. The adoption of this new crop will change the attribute space. This type of land switch to cotton is likely to face more barrier than the business-as-usual land-use switching because

[15] Note that such a super-soybean which has 30% higher stomata density does not exist.

[16] Note that such a chemical spray is hypothetical. In fact, Syngenta and AgroFresh, two leading chemical firms, are developing and commercializing a chemical spray called "Invinsa" to enhance drought and heat tolerance of crops. The merit of this technology is that it can be applied to a wide variety of crops to protect crops from yield loss from drought and heat by 5%-15% by suppressing the release of C_2H_4, which is released under stress to accelerate ripening and reduce yield. Unfortunately, such existing technology only changes crop's biochemical attributes, such as C_2H_4 content, instead of physiological attributes that are used in this paper.

farmer should learn the technology of producing cotton and invest in new equipment of harvest and storage. Therefore, the estimated impacts will be the upper bound of the benefits from expanding crop choice set. Overall, farmland value is increased by 13.8% if farmer can freely switch to any of the twenty-three field crops and pasture. These results should be interpreted with caution, however, as they likely imply that adopting new crops would be similarly profitable under current climate conditions. Although farmers can adopt new crops without climate change, climate change may increase the incentive to adopt new crops and my calculation will quantify this incentive. In a future draft, I plan to calculate the difference in value when adoptions of new crops under climate change versus current conditions.

VI. Conclusion

I model farmland value as a function of crop prices, crop attributes, climate and soil characteristics, and land-use choice. I determine the effects of climate extremes on crop yields and farmland value and estimate the potential benefits from changing crop attributes to adapt to climate change. Since climate extremes, especially drought and temperature deficiency, are detrimental to both crop yields and farmland value, a future warmer and wetter climate is likely to increase crop yields and farmland value. Additionally, selectively changing crop attributes via the adoption of new crops, new varieties, and chemicals will enhance the beneficial impacts of climate change.

This study contributes to the extensive literature using an econometric approach to estimate climate change impacts on agriculture. First, the interactions between crop attributes and climate and soil variables allow me to study the heterogeneous impacts of climate change on farmland value. Second, past adaptation behavior allows me to measure the economic benefits from technological change, which enables the adoption of existing crops at new locations, the adoption of existing crops with genetically enhanced attributes, and the application of chemical spray to enhance attributes of a group of crops. Third, the variation in farmland value is modeled in two dimensions—the temporal variation in farmland value is driven by the temporal variation in crop prices, while the spatial variation in farmland value is driven by the spatial variation in soil and climate. Therefore, this model allows both short-term and long-term adaptation strategies. Fourth, the effect of yields and the effect of land-use change on farmland value are modeled separately, so the model helps to show the connection between the production function approach and the Ricardian approach for estimating the impacts of climate change in agriculture.

This study may provide guidance to policy makers, university extension services, and private industry (e.g., seed firms and investment firms) in helping agriculture to adapt to climate change. Federal, state, and local governments can use the results to determine funding allocations to regions which are most affected. University extensions can use the model to simulate counterfactual local farmland value associated with counterfactual crop choice, predict future land value associated with the best crop choice for local farmers under climate change using detailed local climate and soil characteristics, and guide farmers step-by-step to adapt to climate change by a series of demonstrations. Since extension agents have been identified as a significant source for new technology diffusion (Genius et al 2014; Rivea and Alex 2013), the adoption of new adaptation strategies will rely substantially on university extension services. Agribusiness companies can use the results to decide whether to invest in R&D for new viable crops and varieties and where to introduce the new crops and varieties. Finally, agricultural investment firms can use the results to make farmland acquisition decisions.

Several caveats to this paper's results should be considered. First, the study estimates farmland value and does not provide implications for valuation of forest, urban, and other land-uses. Second, the study does not provide implications on other agricultural outcomes, such as crop prices and ecosystem services. Third, increases in soil moisture and irrigation are important alternative adaptation strategies and should be addressed in further research. Fourth, the role of institutions in assisting farmers to adapt to climate change is also a future research direction.

APPENDICES

APPENDIX 1.1: Derivation of Equation (8) in Chapter 1

Equations (6) and (7) in the main text are rewritten and renumbered as (1') and (2') as below:

(1') $$E(U_c) = E_i[E(U_{ic})] = \sigma \ln\left[\sum_{l\in J} \exp(V_{cl}/\sigma)\right] + constant,$$

(2') $$s_{cj} = E_i\left[\pi_{icj}\right] = \frac{\exp\left[V_{cj}/\sigma\right]}{\sum_{l\in J} \exp[V_{cl}/\sigma]}.$$

I rearrange equation (2') to obtain the following:

(3') $$\sum_{l\in J} \exp[V_{cl}/\sigma] = \frac{\exp\left[V_{cj}/\sigma\right]}{s_{cj}}.$$

Taking the natural log of equation (3'), I obtain equation:

(4') $$\ln\left\{\sum_{l\in J} exp\left[\frac{V_{cl}}{\sigma}\right]\right\} = \frac{V_{cj}}{\sigma} - \ln\left(s_{cj}\right).$$

Multiplying equation (4') by σ on both sides, I obtain equation:

(5') $$\sigma \ln\left\{\sum_{l\in J} exp\left[\frac{V_{cl}}{\sigma}\right]\right\} = V_{cj} - \sigma \ln\left(s_{cj}\right).$$

I then replace $\sigma \ln\left\{\sum_{l\in J} exp\left[\frac{V_{cl}}{\sigma}\right]\right\}$ with $V_{cj} - \sigma \ln\left(s_{cj}\right)$ in equation (1') using equation (5) to obtain equation (8) in the main text:

(8) $$E(U_c) = V_{cj} - \sigma \ln\left(s_{cj}\right) + constant.$$

APPENDIX 1.2: Construction and Sources of Variables

A: Time Varying non-Climate Variables

Source: USDA NASS Quick Stats. http://quickstats.nass.usda.gov/

Land Value: Asset value measured in $/acre on agricultural land and building at county level for 1978, 1982, 1987, 1992, 1997, 2002, and 2007 from Census of Agriculture.

Crop Acreage: Planted acreage for each field crop at county level for 1978, 1982, 1987, 1992, 1997, 2002, and 2007 from Census of Agriculture.

Crop Yield: Yield at county level for 1970-2012 from USDA NASS surveys.

Crop Price: National level crop price for nineteen field crops are obtained during 1970-2012 from Survey of Agriculture.

Per Capita Income: Bureau Economic Analysis, Regional Economic Accounts, table CA1-3.

Population Density: Bureau Economic Analysis, Regional Economic Accounts, table CA1-3. *http://www.bea.gov/iTable/iTable.cfm?ReqID=70&step=1#reqid=70&step=25&isuri=1&7023=7&7024=Non-Industry&7001=720&7090=70&7029=20&7022=20*

Land Area: U.S. Census Bureau 1990.

http://www.census.gov/population/www/censusdata/density.html

B: Time Varying Climate Variables

Source: 1950-2005 monthly PRISM data interpolated to daily data by Schlenker and Roberts (2009) for most of climate variables except day length from Albouy, Graf, Kellogg, and Wolff (2013).

Drought (cm): Cumulative rainfall shortage measured in cm during growing season at county level, measured by the sum of the difference between 0.2 cm and rainfall when rainfall is below 0.2 cm in each day.

Flood (cm): Cumulative rainfall surplus measured in cm during growing season at county level, measured by the sum of the difference between rainfall and 1.7cm when rainfall is above 1.7cm in each day.

Heat (degree Celsius): Cumulative temperature surplus during the growing season at county level, measured by the sum of the degree days above 34°C in each day.

Cold (degree Celsius): Cumulative temperature shortage during the growing season at county level, measured by the sum of the degree days below 0°C in each day.

Sunshine (percentage): average day length (as a percentage of cloud-free hours in a day) during spring, summer, and fall at county level.

C: Time Constant Crop Attributes

Source: USDA Plant Characteristics Database and miscellaneous crop science research via Anderson, Wang, and Zhao (2012)

WUE—Water use efficiency: The ratio of dry matter production and water taken in from the root.

Roots (inches): The minimum depth of soil (in inches) required for good growth, which is the proxy for root depth.

Stomata (# per mm^2): The number of stomata per square mm^2.

Height (feet): The plant's height, measured in feet.

Fibrous Root: A dummy variable which equals one for fibrous root and zero for taproot.

*RUE (g per MJ)—R*adiation use efficiency: the ratio of dry matter production and the photosynthetically active radiation (PAR) energy that is intercepted by plant.

Saturated Fat (percentage): Percentage of saturate fat.

Season (days): The minimum average number of frost-free days within the plant's known geographical range.

Long-day Crop: Plant flowers only when day length is larger than its critical photoperiod.

Min. pH: The plant's minimum tolerant pH.

Max. pH: The plant's maximum tolerant pH.

D: Time Constant Soil Variables

Source: Soil Survey Geographic Database via http://sdmdataaccess.nrcs.usda.gov/Query.aspx

Moisture—AWC (percentage)—Soil available water capacity: the amount of water that an increment of soil can store that is available to plant.

Moisture Squared: AWC squared to capture the concavity of AWC.

pH: The relative acidity or alkalinity of a soil sample.

pH Squared: pH squared to capture the concavity of pH.

Water Erosion—KFF: an erodibility factor which quantifies the susceptibility of soil particles to detachment by water.

Slope (degree): soil slope.

APPENDIX 1.3: Justification for Interactions between Crop attributes and Climate and Soil

Drought×WUE: Crops with high WUE are more sensitive to drought (Delucia and Schlesinger 1991). Negative sign is expected.

Drought×Roots: Long roots help to extract water from underground to resist yield reduction under drought conditions. Positive sign is expected.

Drought×Stomata: Many stomata (work as "pumps") help roots to extract water from underground to resist yield reduction under drought conditions (Xu and Zhou 2008). Positive sign is expected.

Flood×Height: Tall crops expose much shoot in the air to obtain oxygen to resist yield reduction under flood conditions. Positive sign is expected.

Flood×Fibrous Root: Fibrous root exposes more oxygen than taproot to resist yield reduction under flood conditions. Positive sign is expected.

Cold×Growing Season Length: Planting short growing season crops in cold areas potentially resists yield reduction. Negative sign is expected.

Cold×Saturated Fat Content: Planting crops with lower saturated fat content increases cell membrane fluidity in cold areas to resist yield reduction. Negative sign is expected.

Heat×RUE: Planting crops with higher radiation use efficiency (proxy for heat tolerance) in extremely hot areas potentially resists yield reduction. Positive sign is expected.

Heat×Saturated Fat Content: Planting crops with higher saturated fat content (proxy for cell membrane frigidity) in extremely hot areas potentially resists yield reduction. Positive sign is expected.

Sunshine×Long-day Plant: Long-day plant requires long duration of daylight to bloom. Positive sign is expected.

Sunshine×RUE: Planting plant with lower radiation use efficiency in areas with more sunlight increases crop yield. Negative sign is expected.

Moisture×WUE: Crops with high WUE is sensitive to water insufficiency. Positive sign is expected.

Moisture×Roots: Planting crops with longer roots in soil with lower available water capacity can increase crop yield. Negative sign is expected.

Moisture×Stomata: Planting crops with higher stomata density in soil with lower available water capacity can increase crop yield. Negative sign is expected.

pH×1[pH<Min. pH]: Planting crops with higher minimum pH on higher pH can potentially save cost on lime powder. Positive sign is expected.

pH×1[pH>Max. pH]: Planting crops with lower maximum pH on higher pH can potentially incur cost on sulfur or sulfate. Negative sign is expected.

Water Erosion×Roots: Planting crops with deeper root in soil which is more susceptible to water erosion can help to prevent runoff and potentially save cost on erosion protection practice. Positive sign is expected.

Wind Erosion×Roots: Planting crops with deeper root in soil which is more susceptible to wind erosion can help to prevent runoff and potentially save cost on erosion protection practice. Positive sign is expected.

Slope×Roots: Planting crops with longer roots in soil with deeper slope helps to resist erosion. Positive sign is expected.

Slope×Height: Planting short crops in soil with deeper slope helps to resist erosion. Negative sign is expected.

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Chapter 2 Two Birds, One Stone? Biomass Promotion and Deforestation Prevention by the Biomass Crop Assistance Program

Renewable energy policies aim to reduce dependence on imported oil, mitigate greenhouse gas (GHG) emissions, and spur regional economic growth (Energy Policy Act of 2005; Energy Independence and Security Act of 2007; Renewable Fuel Standards 2008). However, one of the central and immediate criticisms in renewable energy development is whether substituting renewable energy for gasoline reduces GHG emissions. Seachinger et. al. (2008) proposes that higher GHG emissions and crop prices would be triggered if farmers divert forest or cropland to biofuels either directly or indirectly. Direct land-use change refers to the direct conversion of an area for biomass production and processing. Indirect land-use change refers to the "displacement effect" or "leakage effect", in which the crop that has been replaced for the bioenergy production is grown at another place to maintain the overall supply of that crop (Roundtable on Sustainable Biofuels 2008). Though the idea of land-use changes has been widely discussed, direct empirical evidence on land-use change by the demand for bioenergy crops is lacking.

Another central issue in renewable energy development is whether the external incentives to promote biomass are indeed effective. Altman, Sanders, and Boessen (2007) propose that asset specificity makes the biomass supply side reluctant to grow dedicated bioenergy crops; therefore, adequate incentives are needed. Notably, a farmer’s decision to switch to biomass production is affected by the form and magnitude of incentives. Song, Zhao, and Swinton (2009) suggest that a short-term monetary subsidy will induce farmers to convert cropland to bioenergy crops in the short run but discourage bioenergy crop supply in the long run. Joskow (1985 and 1987) shows empirical evidence that vertical integration and long-term contracts are more effective than short-term contracts when investments are relationship-specific in the coal market. In the biomass market, where vertical integration is prevalent, empirical evidence on the effectiveness of incentives is lacking.

To address these issues, I empirically estimate of land-use changes induced by the demand for two types of bioenergy crops using a quasi-experimental approach. In 2008, a large-scale co-op cellulosic biomass processing plant opened in central Missouri. Upon opening, the plant began converting food crop residues such as soybean stubble, corn stalk, and wheat straw to pellets for use in bioenergy production. The opening of the plant will likely increase the local production of major food crops due to its permanent, positive shock on the local demand for food crop residues, which are jointly produced with food crops. However, transportation cost increases with distance to the plant and inevitably limit the plant's impact to farmers nearest to the plant. In 2011, the plant sponsored the U.S. first Biomass Crop Assistance Program (BCAP), which provides financial support to the co-op members to grow native perennial grasses, such as switchgrass and big bluestem. The plant along with the BCAP subsidy creates a local market for both food crop residues and native perennial grasses. As with food crop residues, the plant's impact on the production of native grasses will be largest for farmers near the plant, due to high transportation costs to deliver the bulky materials. Therefore, the plant's opening and the subsequent BCAP create plausible exogenous variation in the demand of bioenergy crops for farmers close to versus farmers far away from the plant, enabling the identification of the effects of the plant and BCAP on land-use.

To reveal such effects, in two separate difference-in-differences (DD) regressions, I compare land-use changes for parcels near to and far away from the plant, before and after the plant opening as well as before and after the BCAP offering. I find that the opening of the plant slightly induces land conversion from forest and pasture to food crops, while the BCAP subsidy substantially induces land conversion from pasture to native grasses and food crops, notably without deforestation. The combined findings suggest that the BCAP not only effectively induces bioenergy crop supply, but also deters deforestation for bioenergy crops, while the presence of the co-op plant alone does not defer deforestation.

This paper relates to a broad literature on land-use changes induced by the demand for bioenergy crops. One vein of this literature uses bio-economic models to simulate land-use changes caused by the demand for bioenergy crops. In step one, crop production models such as *Environmental Policy Integrated Climate (*EPIC) are used to simulate bioenergy crop yields and other outcomes as a function of soil, climate, and management decisions. In step two, these results are used as input variables in a mathematical programming model of farmer decisions in order to simulate optimal crop choices at different locations (Egbendewe-Mondzozo et.al. 2011; Larson et.al. 2010; and Mapemba et.al. 2007). The bio-economic models can incorporate many details about crop growth, such as germination and flowering, as well as farm management practices, such as crop rotation and the application of fertilizers, capturing observed regional heterogeneity. However, these models do not address unobserved behavior and sometimes require ad-hoc calibration.

Some researchers rely on partial or Computable General Equilibrium (CGE) models to study land-use changes caused by the demand for bioenergy crops. Many partial or CGE models have been used to estimate the impacts of the Renewable Fuel Standards (RFS) on land-use (Beach and McCarl 2010; Chen, Huang, and Khanna 2012; Chen, Huang, Khanna, and Onal 2014; Ferris and Joshi 2010; Hertel et. al. 2008). Although the partial or general equilibrium models incorporate market dynamics and interactions between sectors and countries, the analysis is only appropriate for aggregated sectors of the economy. Similar to the simulation-based bio-economic models, no unobserved behavior is accounted for in the CGE models.

Some researchers use econometric techniques to predict land-use changes caused by the RFS and the demand for bioenergy crops. Anderson, Wang, and Zhao (2012) develop a novel econometric model to explain the historical crop choice decision as a matching process between crop physiological attributes (e.g. root depth) and climate and soil characteristics. Given the physiological attributes of a new crop, the model can predict where the crop will be adopted and what is displaced as a result. Roberts and Schlenker (2013) study the supply and demand for the total caloric content provided by staple crops and predict that the demand for biofuels expands land area at the extensive margin. Scott (2014) applies a dynamic econometric land-use choice model to study historical land-use patterns and predicts that the demand for biofuels has significant effects on land-use change. Diverging from the simulation approach, these econometric models take unobserved behaviors into account. However, these study focus on prediction. No real land-use changes are observed after the adoption of bioenergy crops.

The last group of research on land-use changes is highly related to this paper, by showing empirical evidence on actual deforestation driven by land-use changes. Barona et. al. (2010) apply Geographic Information System techniques to trace land-use changes in the Amazon. They find a correlation between deforestation and pasture expansion in Legal Amazon. However, they cannot show a causal effect between the two. Arima et al. (2011) employs spatial regression to tackle the causal effect of soy expansion in one place on deforestation at another place. However, similar to Barona et. al. (2010), this study does not focus on land-use changes induced by the demand for bioenergy crops. Remarkably, Andrade de Sá, Palmer, and di Falco (2013) show the first evidence of deforestation in Amazon indirectly caused by the expansion of sugarcane, a traditional cultivated bioenergy crop, in the South Brazil.

Last, this paper is highly related to the literature on policy intervention to reduce deforestation. Burgess et. al. (2011) proposes that local officials' incentives affect deforestation in Indonesia. Jayachandran (2013) shows that payment for deforestation prevention has limited effectiveness in Uganda where farmers are liquidity constrained. Alix-Garcia, Sims, and Yanez-Pagans (2015) find that a Mexico's payment to land owners for forest protection not only deters deforestation but also alleviates poverty. Here, I evaluate of the effectiveness of a policy to prevent deforestation in the context of biomass development, which could potentially stimulate deforestion.

This study adds two contributions. First, this study provides direct empirical evidence for land-use changes caused by the demand for bioenergy crops. By comparing land-use change near to and far from the plant, before and after the presence of the plant and the BCAP subsidies, the study uses variation in the local demand for bioenergy crops both over time and across space, purging cross sectional omitted variable bias. Although the *predicted* impact of the demand for bioenergy crops on land-use changes has been intensively studied, few have evaluated the *actual* impact of the demand for bioenergy crops. Second, this study shows that the form and magnitude of incentives for land conversion are important. The establishment of the local biomass market induces land conversion from forest and pasture to food crops, while the biomass subsidy induces land switch from pasture to native grasses and food crops.

The remainder of the paper is structured as follows. Section I introduces BCAP. Section II describes the local study area and data. Section III describes the estimation strategies (difference-in-differences). Section IV presents main estimation results and robustness checks. Section V concludes with discussion.

I. Background of BCAP

The RFS mandates 16 billion gallons of cellulosic biofuels by 2022. This requires large production of biomass feedstocks that have never been cultivated in history. There are several concerns in promoting bioenergy production, one being the effectiveness of promotion incentive. Due to the lack of a spot market, both the supply side and the demand side are reluctant to enter the biomass business. To overcome the chicken-and-egg challenge in biomass market, the 2008 Farm Bill establishes the BCAP to provide financial support to agricultural and non-industrial private forest owners and operators to produce eligible bioenergy crops (U.S. Congress 2008). Eligible bioenergy crops include any perennial and annual crops with renewable biomass, except crops[1] which are eligible for payments under Title I of the 2008 Farm Bill, and invasive and toxic crops. Eligible lands include a broad range of cropland, grassland, pastureland, hay land, and forest land but exclude land currently enrolled in the Conservation Reserve Program (CRP), Grassland Reserve Program (GRP), Wetland Reserve Program (WRP), and other similar programs. In addition, contracted biomass producers in the project area should follow conservation and forest stewardship plans.

Farmers who grow eligible bioenergy crops may receive three types of BCAP payments: a matching payment, an establishment payment, and an annual payment. The matching payment is made to biomass suppliers for their effort to collect, harvest, store, and transport bioenergy crops after they deliver biomass to designated biomass conversion facilities. The establishment payment

[1] Ineligible crops include but are not limited to: barley, corn, grain sorghum, oats, rice, or wheat; honey; mohair; certain oilseeds such as canola, crambe, flaxseed, mustard seed, rapeseed, safflower seed, soybeans, sesame seed, and sunflower seeds; peanuts; pulse crops such as small chickpeas, lentils, and dry peas; dairy products; sugar; wool; and cotton boll fiber (USDA Farm Service Agency, Biomass Crop Assistance Program Handbook 2011).

is made to biomass producers to prepare sites, purchase seeds, and plant perennial crops. The annual payment is a soil rental rate for producing annual or perennial bioenergy crops.

In order to receive BCAP subsidy, a sponsor—either a biomass conversion facility or a group of farmers—proposes a BCAP project area to the USDA Farm Service Agency. The sponsor specifies eligible bioenergy crops that are attractive to farmers in a proposed geographical boundary that should be within a practical distance to the sponsor's biomass conversion facility. The sponsor also obtains a commitment from a biomass conversion facility to use these bioenergy crops. Once the project is approved, farmers within this boundary are eligible to sign a 5-year contract to produce eligible annual bioenergy crops or a 15-year contract to produce eligible perennial bioenergy crops with the Farm Service Agency. When the farmers become BCAP contracted biomass producers, they will receive a reimbursement of up to 75 percent of the establishment costs and an annual payment within the contract duration period. Also, any biomass producer, regardless of being contracted, is eligible for a matching payment that matches the price received at the biomass conversion facility with a 1-to-1 rate up to $45 per dry ton for up to two years.

II. Local Study Area and Data

The BCAP structure provides variation that allows me to study land-use change induced by the demand for bioenergy crops, incentives to develop the biomass market, and approaches to deter deforestation. As of March 2015, there are eleven BCAP project areas in the United States. However, only the BCAP Project Area One provides panel data with sufficient years to study the aforementioned issues. Therefore, this paper focuses on the geographic area near the BCAP Project Area One.

A. Show Me Energy Cooperative

Responding to the call for a cleaner environment, in 2008, Steven Flick, the owner of a local seed company in central Missouri, founded the Show Me Energy Cooperative, which is the first U.S. producer-owned biomass co-op. Since its establishment, the co-op plant has processed food crop residues such as soybean stubble, corn stalk, and wheat straw into pellets for its members. The pellets are then transported to Kansas City Power and Light Company to generate electricity.

To be able to deliver biomass to the co-op plant, each member must pay an up-front membership fee. Each member's maximum delivery is a function of his membership contribution. In particular, every dollar equates to five pounds of biomass. So, for example, a farmer who pays a $5,000 entry fee is eligible to deliver 25,000 pounds of biomass to the plant, while a farmer who pays a $10,000 membership fee is eligible to deliver 50,000 pounds of biomass to the plant. Contributions are limited to $5,000 increments. Thus, the membership fee is equal to $0.2 per dry ton, with a minimum of 25,000 tons to deliver (Stelzer 2008).

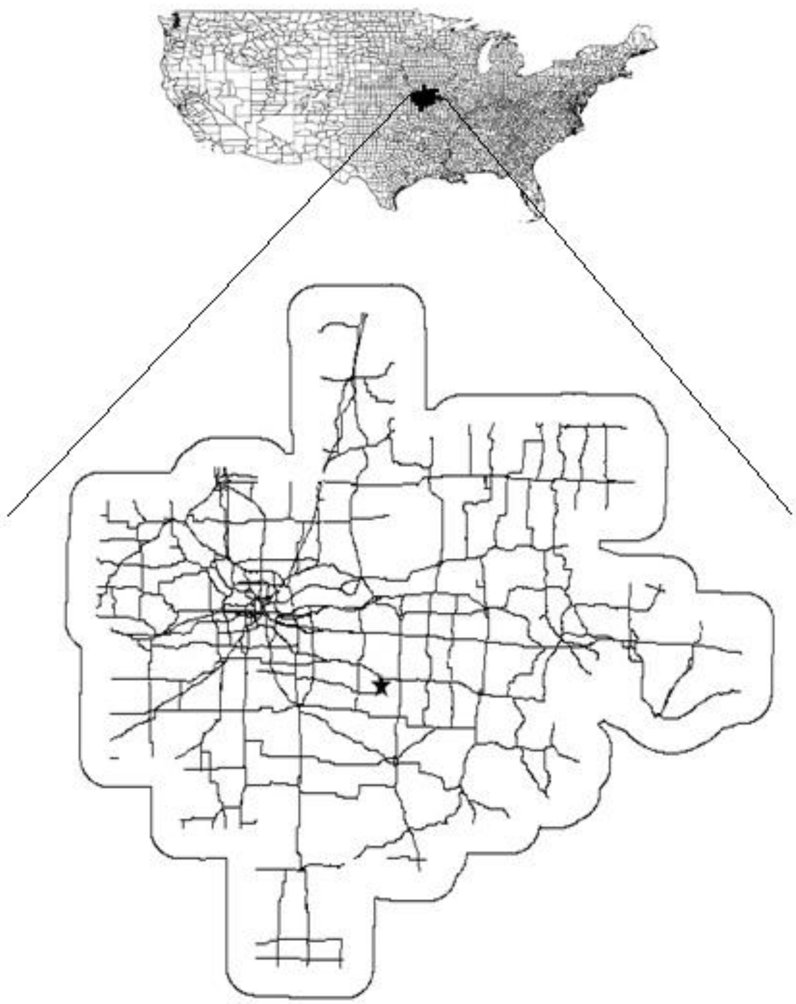

Figure 2.1 Study Area: BCAP Project Area One and 10 Miles Beyond The BCAP Boundary

Note: This figure represents the study area, which includes the BCAP Project Area One and 10 miles outside the BCAP boundary. The icon represents the plant location and the lines inside represent road networks within the BCAP boundary.

B. BCAP Project Area One

In 2011, the co-op sponsored the first BCAP Project Area, which consists of 39 counties in Kansas and Missouri. Figure 2.1 shows the study area, which includes the BCAP Project Area One and 10 miles outside of the BCAP boundary. The icon at the center of the figure marks the location of the sponsor co-op plant and the interacted lines represent major roads in the BCAP Project Area

One. The first-year enrollment was 20,000 acres of native perennial grasses, such as switchgrass and Indian bundleflower, legumes, and forbs. This area represents 3.5 percent of the land area within 30 miles of the plant, and 1.3 percent of the land area within 50 miles of the plant. For comparison, the estimated land needed for bioenergy crop production to meet the legislated RFS mandate for cellulosic ethanol production (prior to the EPA granting waivers) accounts for 2.3 percent[2] of total U.S. arable land. Thus, in relative terms, the scale of biomass production in BCAP Project Area One is roughly comparable to that of the RFS mandate.

To address concerns that biomass production might lead to cropland diversion and deforestation, specific rules apply to the BCAP Project Area One. In addition to the BCAP general rules on land exclusion of CRP and equivalent programs, the BCAP Project Area One excludes BCAP subsidies for private forest lands, lands with 20 percent or more of woody cover canopy, native sod, and land owned by government agencies. The annual payment rates are determined by 1) the non-irrigated cropland soil rental rates for cropland with 5 percent or less tree canopy and 2) the lowest county marginal pasture land rental rate for cropland with more than 5 percent but less than 20 percent tree canopy, grasslands, hay lands, pasture lands, range lands or similar lands. All BCAP contracted biomass producers receive an additional 20 percent incentive premium on top of the annual payment rate (USDA 2011). Though soybean stubble, cornstalk, and wheat straw are not eligible for BCAP subsidies, they are acceptable at the sponsor plant as before the presence of the BCAP.

[2] I assume 1.7 billion acres arable land, which includes forest, pasture, and cropland in the United States. (Lubowski et. al. 2006), 4.5 tons per acre of biomass yield (Wullschleger et. al. 2010), 90 gallons per ton conversion rate from biomass to ethanol (National Renewable Energy Laboratory 2007), and 16 billion gallons cellulosic ethanol for the mandate (RFS 2008). I calculate $\frac{16\ billion\ gallons*100\ percent}{90gallons/ton*4.5tons/acre*1.7\ billion\ acres} = 2.3\ percent.$

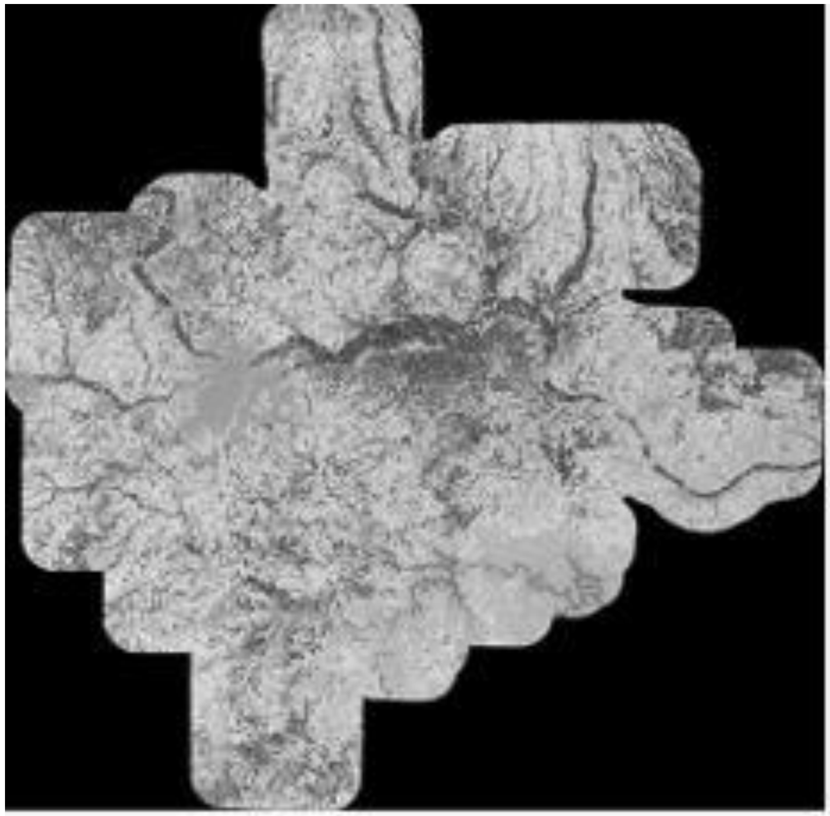

Figure 2.2 Parcel Level Land-use Data in Study Area (2013)
Source: USDA National Agricultural Statistics Service Cropland Data Layer. 2014.

Note: This figure shows the visual representation of the land-use at the parcel level in the study area, which is the BCAP Project Area One and 10 miles outside the boundary. Each parcel represents a 30m by 30m area in 2013.

C. Data

Land Cover Data. — Sample land-use data are extracted from CropScape, a satellite-based Cropland Data Layer (CDL) raster database that contains over thirty unique land cover types in Missouri and Kansas for 2006-2014. The geospatial database identifies each raster cell with a land cover type, a land cover code, and a color that represents a land cover type such as corn or soybeans. Definitions of land cover types used in this study are in Appendix 2.1. Figure 2.2 shows the visual land-use data in BCAP Project Area One in 2012. In total, the study area contains approximately 96 million raster cells in 2010-2014 and 27 million raster cells in 2006-2009. The difference in the numbers of raster cells is attributed to different resolutions in different years. The resolution for 2010-2014 is 30m by 30m, whereas the resolution for 2006-2009 is 56m by 56m.

To make sure the data are consistent from year to year, instead of using raster cells directly, I randomly sample 1 million points using ArcGIS, which I refer as sample points. The sample includes 978,324 points excluding points covered by clouds, which cannot be identified for land cover type. The sampled points can be uniquely identified by their latitudes and longitudes and therefore are consistent from year to year. There are two advantages of using these sampled points instead of the original raster cells. First, I avoid inconsistency in the cell sizes in different years. Second, the sampled points are typically from non-adjacent parcels, potentially mitigating the problems related to spatial spillovers for adjacent cells or cells that are in close proximity.

Grouping of land cover categories is required to mitigate the data measurement errors in the CDL. Data measurement error occurs, for example, when the satellite attempts to distinguish between grass types. Johnson (2011) finds that the probability that a parcel has been correctly identified is 60 percent for hay and 76.7 percent for pasture at the national level. However, in particular states, the accuracy could be as low as 20 percent. Since categorization of grass types is least accurate, I group pasture/hay, pasture/grass, grass/herbaceous, and alfalfa into a single category called “pasture”. Similarly, I group deciduous forest, evergreen forest, and mixed forest into “forest” and group herbaceous wetlands and woody wetlands into “wetlands”. To be consistent, I also created a group called “major food crops” that includes soybeans, corn, wheat, double cropping – soybeans and wheat.

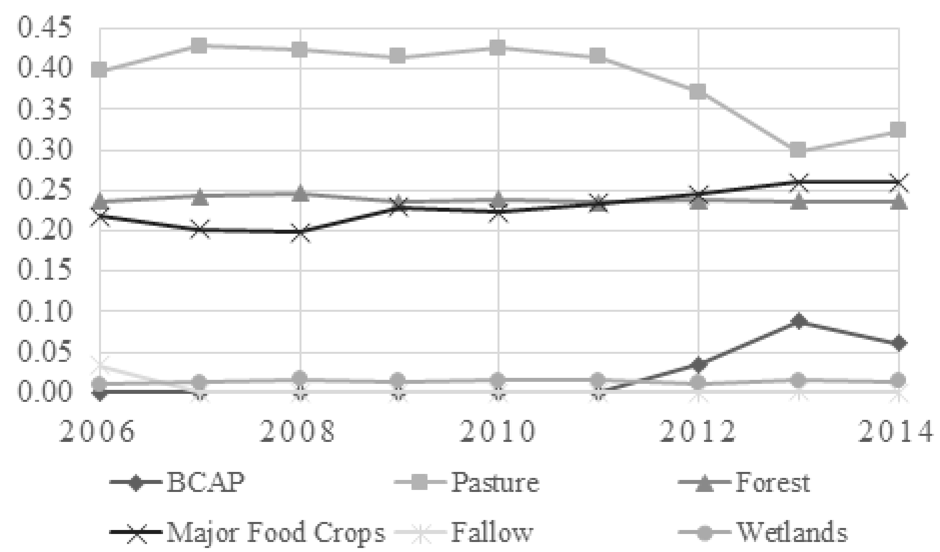

Figure 2.3 Land-use Shares in The Study Area from 2006 to 2014

Note: This figure shows the land-use shares of the six categories of interest in the study area from 2006 to 2014.

The CDL does not include a specific category for the types of native grasses eligible for BCAP subsidy. However, two pieces of evidence suggest that such native grasses are included in the “non-alfalfa hay” category. First, according to USDA Farm Service Agency, grasses and mixed forage belong to the non-alfalfa hay category. Second, the non-alfalfa hay category in the CDL has zero counts before the BCAP debut but positive counts after the presence of the BCAP. The timing of the presence of the non-alfalfa hay category coincides with the presence of BCAP in this region. Therefore, it is reasonable to believe that the native grasses belong to the non-alfalfa hay category in the CDL. To emphasize that this category includes BCAP eligible crops, I name it "BCAP crops".

Figure 2.3 shows the land-use shares for each of the six categories of interest − BCAP crops, pasture, forest, major food crops, fallow, and wetlands, which together account for 90 percent of land-use in the study area from 2006 to 2014. Pasture is ranked as the leading land-use choice, followed by forest, major food crops, wetlands, and fallow in 2006-2011. From 2011 to 2014, pasture decreases by 9 percent, BCAP crops increase by 6 percent, and major food crops increase slightly by 3 percent.

Distance. — Distance from a sample point to the plant is measured by the Euclidean distance in miles and calculated with ArcGIS.

Soil Characteristics. — Soil data include soil moisture (Available Water Capacity), Organic Matter, CACO3, Water Erosion Index, and Wind Erosion Index. The original soil data are downloaded from the grid USDA Soil Survey Geographic Database (gSSURGO) and aggregated to county level.

Climate Characteristics. — Climate data include drought (daily precipitation < 2mm), flood (daily precipitation > 17mm), average temperature, and temperature surplus (Degree Days > 34ºC). The original weather data are PRISM monthly average temperature and precipitation data at each 30m by 30m grid. Schlenker and Roberts (2009) interpolated the data to daily data, which are then aggregated to county level (Anderson, Wang, and Zhao 2012).

III. Econometric Model

The land-use changes induced by the demand for bioenergy crops can be identified using the variation in distance to the plant, before and after the plant and BCAP subsidies began. The demand for food crop residues is boosted by the emergence of the plant and the demand for native grasses is induced both by the plant and the BCAP subsidies. After the presence of the plant, land parcels that are closer to the plant will incur lower transportation costs than parcels that are far away, all else equal. Hence, by comparing land-use changes between parcels that are close to versus far from the plant, before and after its opening, I can identify the extent to which local land-use changes are caused by the local demand for food crops. Also, the BCAP provides subsidies to support production of native grasses. Hence, by comparing land-use changes between parcels that are close to versus far away from the plant, before and after the presence of BCAP subsidies, I can identify the land-use changes induced by the BCAP subsidies.

A. Difference-in-Differences Model

To eliminate time-series correlation present in the annual data, following Bertrand, Duflo, and Mullainathan (2004), I separately average the variables for years within three periods. I define 2006-2007, 2008-2011, and 2012-2014 as pre-, mid-, and post- policy periods respectively. During

2006-2007, neither the plant nor the BCAP exists. During 2008-2011[3], the plant is established while the BCAP is not[4]. During 2012-2014, both the plant and the BCAP are present.

I then specify the probability of growing crop i on a parcel of land j at time t in a linear probability model:

$$(1) \qquad p_{ijt} = \alpha_i + \beta_i \cdot MID_t + \gamma_i \cdot POST_t + \kappa_{ij}$$
$$+f\left(DISTANCE_j; MID_t\right) + g\left(DISTANCE_j; POST_t\right) + \varepsilon_{ijt},$$

where $p = 1$ if land-use i appears in parcel j at time t and $p = 0$ otherwise; MID is a dummy variable that equals 1 for the periods after the plant has been established and 0 otherwise; $POST$ is a dummy variable that equals 1 for periods after the BCAP subsidies are implemented and 0 otherwise; κ is a parcel fixed effect that captures time-invariant unobserved effects, such as soil quality at parcel level; $f\left(DISTANCE_j; MID_t\right)$ is the effect of distance on land-use between the pre- and mid- periods; $g\left(DISTANCE_j; POST_t\right)$ is the effect of distance on land-use between the mid- and post- periods, and ε is the random error.

In equation (1), β captures the aggregate effect between the pre- and mid- policy periods, which includes the finalization of RFS, the rise in food crop prices, and the increase in crude oil prices; γ captures the aggregate effect between the mid- and post- policy periods, which includes the finalization of RFS2, the further rise in food crop prices, and the further increase in crude oil

[3] Though the BCAP was implemented in 2011, the bioenergy crops planted in November 2011 are not recorded by the satellite which records crop production in June. Therefore, the bioenergy crops planted in 2011 will be recorded in 2012.
[4] The matching payment was first implemented in 2009, suspended in 2010, and reinstated in 2011. The establishment and annual payment was implemented in 2011.

price; $f(DISTANCE; MID)$ captures the added effect of distance to the plant between the pre- and mid- policy periods; and $g(DISTANCE; POST)$ captures the added effect of distance to the plant between the mid- and post- policy periods.

B. Identifying Assumptions

$$(2) \qquad E\left(\varepsilon_{ijt} | MID_t, , POST_t, \kappa_{ij}, f\left(DISTANCE_j; MID_t\right), g\left(DISTANCE_j; POST_t\right)\right) = 0.$$

The above assumption is necessary for model in equation (1) to yield unbiased estimates. By differencing between any two periods, and including a constant term, the parcel fixed effect and any aggregated trends can be flushed out, leaving only differential trends across different locations. Thus, the key assumption is of "parallel trends" in land-use across different locations (i.e., an error term that uncorrelated with distance effects, conditional on the aggregate time trends and parcel fixed effects). Parallel trends implies that land-use change at a given proximity would have been similar to land-use change closer or further away from the plant, on average, had there been no plant or BCAP. The parallel trends do not require that there is no trend in land-use choice before the opening of the plant and the BCAP. The parallel trends also do not require land-use shares be the same for all parcels regardless of distance to the plant before the opening of the plant and the BCAP. Though the parallel trends cannot be formally tested, there are a few ways to informally test the assumption. One of the methods is to plot the outcome variables against time for the treatment group and control group (here, plants close to versus far away from the plant) and check if the pre-treatment trends in two groups are parallel. Another way to is to test whether the exogenous time-varying characteristics of the parcels near the plant change in the same way as the characteristics of the parcels far away from the plant, before and after the policies.

IV. Estimation Results

The main data sample used in this paper is restricted to parcels within 50 miles from the plant because it is not cost-effective to transport energy crops to longer distance (Atchison and Hettenhaus 2003; English et. al. 2006; Khanna et. al. 2008; Larson et. al. 2010). Since all parcels within 50 miles from the plant are also within the BCAP boundary, this implies that the parameters identified are conditioned on parcels eligible for BCAP[5].

A. Parallel Trends

Local polynomial regression is applied to plot the land shares as a function of distance to the plant for each of the six land-use categories. Figure 2.4 shows the land shares for the six categories as a function of distance to the plant in 2006-2007. The curves in tight dot and dash represent land-uses in 2006 and 2007 respectively. The difference between any two curves in each graph represents the time trend for the specific land-use at the specific distance to the plant. As can be seen, for all six land-use categories, land share changes similarly from 2006 to 2007 at different distances. Figure 2.5 shows the land shares for the six categories as a function of distance to the plant in 2008-2011. The curves in tight dot, short dash dot, long dash dot, and solid represent land-

[5] An earlier version of the paper estimated the effects of the BCAP subsidies using the discontinuity in the eligibility boundary, finding a zero effect as expected.

uses in 2008 to 2011 in figure 2.5. Similarly, for all six land-use categories, land share changes similarly from 2008 to 2011 at different distances, except pasture in 2008.

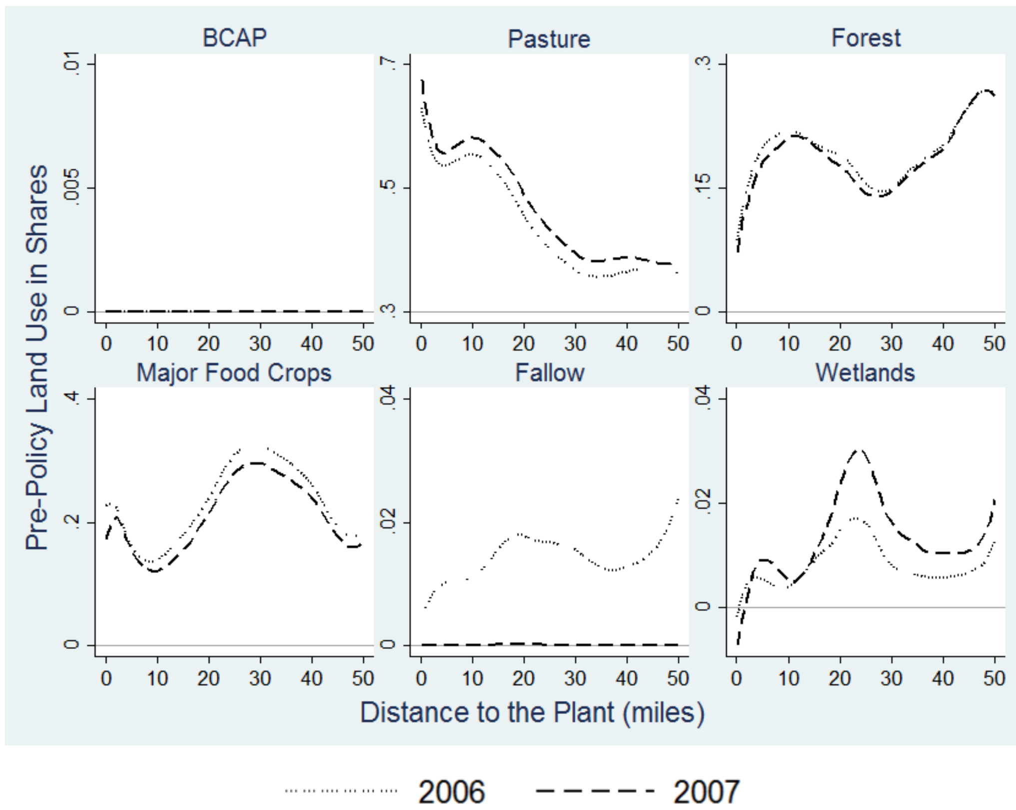

Figure 2.4 Land-use Shares Versus Distance to The Plant During Pre-Policy Years

Note: This figure presents land-use shares versus distance to the plant during the pre-policy years using local polynomial regressions. The vertical axes represent land-use shares for each of the six categories and the horizontal axes represent distance to the plant.

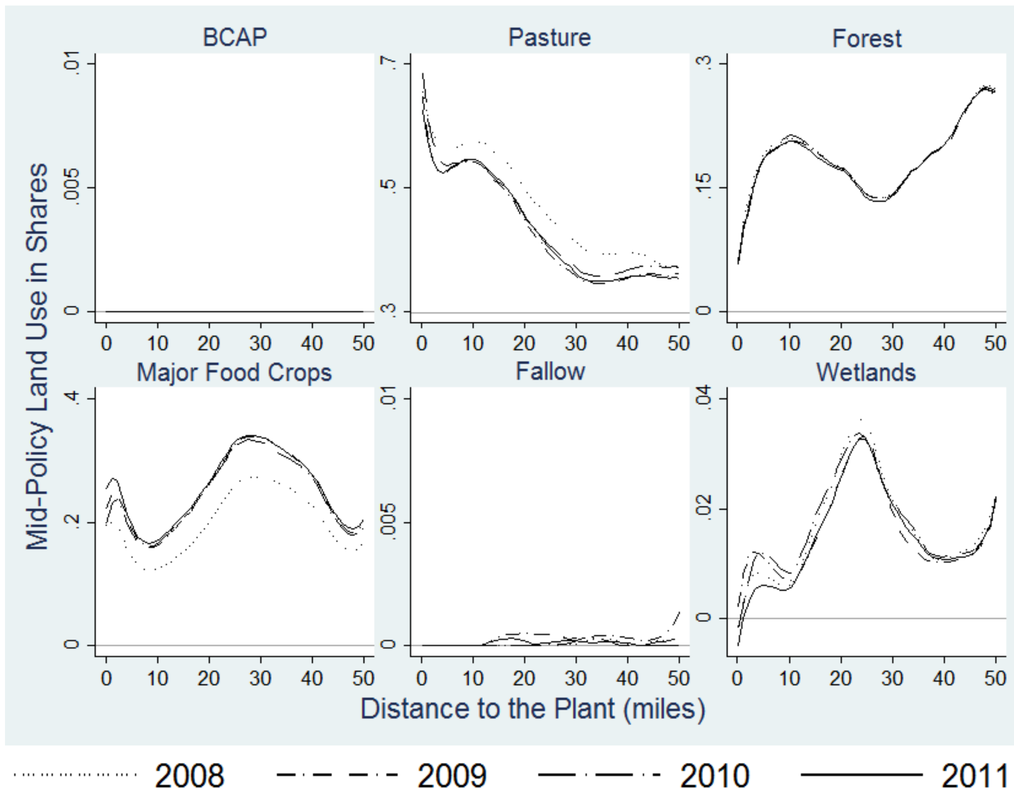

Figure 2.5 Land-use Shares Versus Distance to The Plant During Mid-Policy Years

Note: This figure presents land-use shares versus distance to the plant during the mid-policy years using local polynomial regressions. The vertical axes represent land-use shares within their own max-min ranges for each of the six categories and the horizontal axes represent distance to the plant.

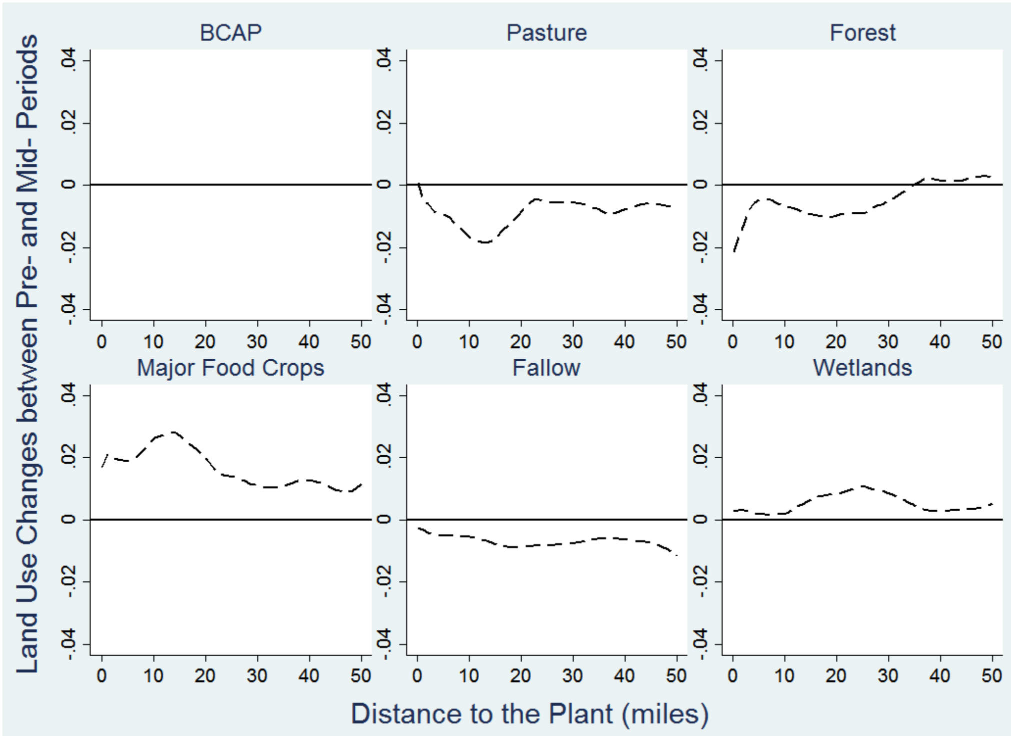

Figure 2.6 Changes in Land-use Shares Versus Distance to The Plant Between Pre- and Mid-

Note: This figure presents the changes in land-use shares versus distance to the plant between pre- and mid-policy periods using local polynomial regressions.

Figure 2.6 plots a detailed relationship between the land-use changes and the distance to the plant between pre- and mid- policy periods. The dashed lines show the proximity effect on land-use changes for parcel points. The gray horizontal line represents zero changes in land-use. As can be seen, moving closer to the plant, forest and pasture decrease while major food crops and fallow cropland increase.

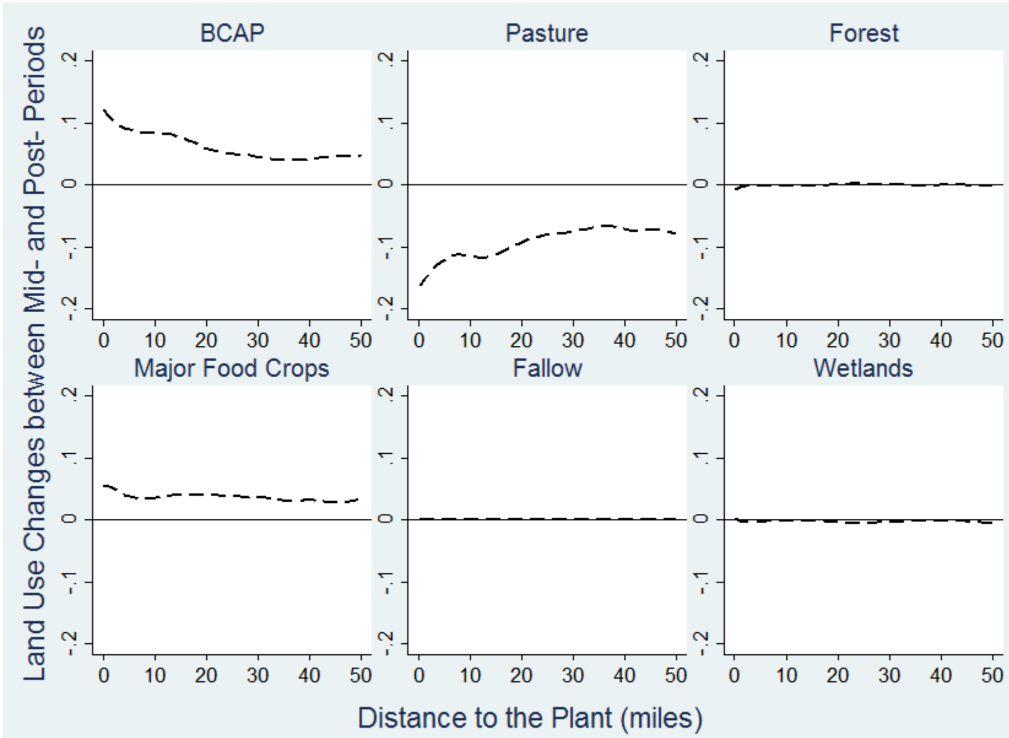

Figure 2.7 Changes in Land-use Shares Versus Distance to The Plant Between Mid- and Post-Policy Periods

Note: This figure presents the changes in land-use shares versus distance to the plant between mid- and post-policy periods using local polynomial regressions.

Figure 2.7 plots a detailed relationship between the land-use changes and the distance to the plant between mid- and post- policy periods. As can be seen, moving closer to the plant, pasture decreases while BCAP crops and major food crops increase (albeit slightly).

Table 2.1 Land-Use Shares Before and After the Plant Opening between Pre- and Mid- Policy Periods

Distance to co-op	NEAR(0-5 miles)			FAR(45-50 miles)			
	Before	After	Change	Before	After	Change	Diff-in-Diff
BCAP	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pasture	54.42	53.25	-1.17	36.80	36.16	-0.63	-0.54
Pasture/Hay	43.69	53.16	9.47	28.44	34.65	6.21	3.26
Pasture/Grass	10.63	0.00	-10.63	7.32	1.32	-6.00	-4.63
Grass Herbaceous	0.10	0.09	-0.01	1.02	0.19	-0.83	0.82
Alfalfa	0.00	0.00	0.00	0.02	0.01	-0.01	0.01
Forest	17.00	16.35	-0.65	27.09	27.37	0.28	-0.93
Deciduous Forest	16.96	16.34	-0.62	26.67	26.71	0.04	-0.66
Evergreen Forest	0.00	0.01	0.01	0.39	0.62	0.23	-0.22
Mixed Forest	0.04	0.00	-0.04	0.03	0.05	0.01	-0.05
Major Food Crops	20.15	22.26	2.11	16.53	17.37	0.84	1.27
Soybeans	11.01	14.01	2.99	8.90	9.85	0.96	2.04
Corn	8.41	7.58	-0.82	6.07	6.44	0.37	-1.20
Double Cropping -	0.51	0.39	-0.12	1.13	0.81	-0.32	0.20
Wheat	0.22	0.29	0.06	0.43	0.26	-0.17	0.23
Fallow	0.45	0.00	-0.45	0.89	0.03	-0.87	0.42
Wetlands	0.69	1.02	-0.33	1.05	1.44	-0.38	0.06
Woody Wetlands	0.02	0.05	0.03	0.08	0.13	0.05	-0.02
Herbaceous Wetlands	0.67	0.97	0.30	0.97	1.31	0.33	-0.04
Other	7.29	0.03	-7.26	17.64	0.07	-17.57	10.31

Note: This table presents the land-use shares and land-use change for parcels close to and far from the plant during the pre- and mid- policy periods. The second to the fourth columns present land-use shares in pre-policy period, mid-policy period, and land-use change between pre- and mid- policy periods for parcels within 5 miles of the plant. The fifth to the seventh columns present land-use shares in pre-policy period, mid-policy period, and land-use change between pre- and mid- policy periods for parcels within 45-50 miles of the plant. The last column presents the rough estimate of the difference-in-differences parameter of being close to the plant.

Table 2.2 Land-Use Shares Before and After the Plant Opening between Mid- and Post- Policy Periods

Distance to co-op	NEAR(0-5 miles)			FAR(45-50 miles)			
	Before	After	Change	Before	After	Change	Diff-in-Diff
BCAP	0	9.12	9.12	0	4.61	4.61	4.51
Pasture	53.25	40.13	-13.12	36.16	28.83	-7.34	-5.78
Pasture/Hay	53.16	20.28	-32.88	34.65	15.46	-19.18	-13.7
Pasture/Grass	0	0	0	1.32	0.1	-1.22	1.22
Grass Herbaceous	0.09	0.04	-0.05	0.19	0.06	-0.13	0.08
Alfalfa	0	0.02	0.02	0.01	0.02	0.01	0.01
Forest	16.35	16.23	-0.12	27.37	27.23	-0.14	0.02
Deciduous Forest	16.34	16.23	-0.11	26.71	26.53	-0.17	0.06
Evergreen Forest	0.01	0	-0.01	0.62	0.65	0.03	-0.04
Mixed Forest	0	0	0	0.05	0.05	0.01	-0.01
Major Food Crops	22.26	27.24	4.98	17.37	20.28	2.91	2.07
Soybeans	14.01	15.76	1.75	9.85	10.98	1.13	0.62
Corn	7.58	9.93	2.35	6.44	7.75	1.3	1.05
Double Cropping -	0.39	1.12	0.73	0.81	1.25	0.43	0.3
Wheat	0.29	0.43	0.14	0.26	0.3	0.05	0.1
Fallow	0	0	0	0.03	0.02	0	0
Wetlands	1.02	0.49	0.53	1.44	1.15	0.29	0.24
Woody Wetlands	0.05	0	-0.05	0.13	0.11	-0.02	-0.03
Herbaceous Wetlands	0.97	0.49	-0.48	1.31	1.04	-0.27	-0.21
Other	0.03	0.03	0	0.07	0.03	-0.04	0.04

Note: This table presents the land-use shares and land-use change for parcels close to and far from the plant during the mid- and post- policy periods. The second to the fourth columns present land-use shares in mid-policy period, post-policy period, and land-use change between mid- and post- policy periods for parcels within 5 miles of the plant. The fifth to the seventh columns present land-use shares in mid-policy period, post-policy period, and land-use change between mid- and post- policy periods for parcels within 45-50 miles of the plant. The last column represents the rough estimate of the difference-in-differences parameter of being close to the plant.

C. Simple Difference-in-Differences Results

Table 2.1 shows the land-use shares of the major land cover types[1] in two groups: within 0-5 miles and within 45-50 miles from the plant during the pre- and mid- policy periods. The first group represents land shares for parcels close to the plant and the second group represents land shares for parcels far away to the plant. The simple DD estimates show that proximity to the plant is associated with increases in major food crops by 1.27 percent, fallow cropland by 0.42 percent, and wetlands by 0.06 percent and that proximity to the plant is associated with decreases in forest by 0.93 percent and pasture by 0.54 percent. Generally, land has been transferred from forest and pasture to major food crops from the 2006-2007 period to the 2008-2011 period.

Table 2.2 shows the land-use shares of the major land cover types in two groups: within 0-5 miles and within 45-50 miles from the plant during the mid- and post- policy periods. The first group is to represent land parcels close to the plant and the second group is to represent land parcels far away to the plant. The simple DD estimates show that proximity to the plant is associated with increases in BCAP crops by 4.51 percent and major food crops by 2.07 percent and that proximity to the plant is associated with decreases in pasture by 5.78 percent. Generally, land has been transferred from pasture to BCAP crops and major food crops from the 2008-2011 period to the 2012-2014 period.

[1] The distinction between pasture/hay and pasture/grass does not lie in the crop types, but in use. For example, switchgrass can be used for both grazing and hay production.

D. DD Fixed Effect Linear Regression Results

There are several benefits of using DD panel regression over the graphs and the simple DD. First, it facilitates the calculation of the robust standard errors to account for spatial correlation. In particular, standard errors are clustered at the county level to control for within county spatial correlation. Second, it allows multiple periods (pre, mid, and post) which are suitable in this paper. Third, it allows for variation in treatment intensity by allowing continuous distance to the plant instead of a dummy variable to show the proximity to the plant. Fourth, it allows time-invariant individual unobserved heterogeneity which will be eliminated with fixed effect or first differencing regressions. Therefore, in this section, I conduct a DD fixed effect regression.

As to the functional form, I assume a linear relationship between land-use choice and distance to the plant. I then specify a linear probability model of land-use choice as in (3). A linear fixed effect regression is performed for each land-use choice respectively. The coefficient δ captures the linear effect of distance to the plant on land-use choice between the pre- and mid- policy periods and θ captures the linear effect of distance to the plant on land-use choice between mid- and post-policy periods.

(3)
$$p_{ijt} = \alpha_i + \beta_i \cdot MID_t + \gamma_i \cdot POST_t + \kappa_{ij}$$
$$+\delta_i \cdot MID_t \cdot DISTANCE_j + \theta_i \cdot POST_t \cdot DISTANCE_j + \varepsilon_{ijt},$$

Table 2.3 Effects of Distance to the Plant on Land-use Change (Fixed Effect)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
MID × DISTANCE (δ)	0.0000	0.0002	0.0004**	-0.0004**	-0.0000	-0.0001
	(.)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
POST × DISTANCE (θ)	-0.0009*	0.0010*	-0.0000	-0.0003*	-0.0000	0.0000
	(0.0004)	(0.0005)	(0.0001)	(0.0002)	(0.0000)	(0.0000)
MID (β)	-0.0000	-0.0132**	-0.0143**	0.0259***	-0.0067***	0.0088
	(.)	(0.0052)	(0.0059)	(0.0037)	(0.0019)	(0.0057)
POST (γ)	0.0790***	-0.1133***	0.0002	0.0442***	0.0003*	-0.0029
	(0.0144)	(0.0159)	(0.0025)	(0.0051)	(0.0001)	(0.0020)
Constant	0.0000	0.4072***	0.2008***	0.2334***	0.0075***	0.0114***
	(0.0020)	(0.0041)	(0.0017)	(0.0023)	(0.0006)	(0.0011)
Observations	706,053	706,053	706,053	706,053	706,053	706,053

Note: This table shows the regression results using fixed effect difference-in-differences regression. δ and θ are the slope parameters, which represent the effects of a positive distance to the plant on land-use change between pre- and mid- policy periods and between mid- and post- policy periods respectively. β and γ are the time trend parameters, which represent changes between pre- and mid- policy periods and between mid- and post- policy periods at a distance of zero. Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

Table 2.3 presents the effects of distance to the plant on land-use changes using fixed effect regression on each land-use respectively. From the pre period to the mid period, at the plant (i.e., at a distance of zero), major food crops increase by 2.59 percentage points, while forest, pasture, and fallow decreases by 1.43, 1.32, and 0.67 percentage points (the coefficients on MID). Thus, there is a net land transfer from forest, pasture and fallow to major food crops. As distance to the plant increases, forest increases while major food crops decreases, on a roughly one-to-one basis (the coefficients on $MID \times DISTNANCE$), with an implied impact radius of 65 miles from the plant (i.e., when net impacts fall to zero). Thus, proximity to the plant is associated with a decrease in forest and an increase in major food crops during this period.

Similarly, from the mid period to the post period, at the plant, BCAP crops increase by 7.90 percentage points and major food crops increase by 4.42 percentage points, while pasture decreases by 11.33 percentage points (the coefficients on $POST$). Thus, there is a net land transfer to BCAP crops and major food crops from pasture. As distance to the plant increases, pasture increases while BCAP crops and major food crops decrease (the coefficients on $POST \times DISTANCE$), with an implied impact radius of roughly 110 miles from the plant (i.e., when net impacts fall to zero). Thus, proximity to the plant is associated with a decrease in pasture and an increase in BCAP and major food crops during this period. Moreover, the BCAP subsidies have enlarged the size of the area impacted by the plant.

The above joint results have several implications. First, without BCAP, the plant induces land transfer from forest and pasture to major food crops at the plant, while as distance to the plant increases, land is mainly converted from forest to major food crops, within an effective impact radius of 65 miles. Second, the BCAP is effective in inducing the production of bioenergy crops. Though the plant opens in 2008, it has not successfully attracted farmers to grow bioenergy crops until the debut of the BCAP. Additionally, the BCAP subsidies have expanded the area impacted by the plant. Third, by explicitly excluding forest land from the BCAP subsidy, the BCAP effectively deters deforestation for BCAP crops. Fourth, surprisingly, with the BCAP, land transfer from forest to major food crops slows. One of the possibilities is that farmers are forward looking and expect crop residues to become eligible for BCAP soon. Recall that biomass crops that are grown on forestland are not eligible for BCAP subsidies. If farmers grow major food crops on forest land, then the crop residues that are delivered to the plant are not eligible for the BCAP subsidies. Though crop residues are not eligible for BCAP subsidies during 2006-2013, they become eligible in the 2014 Farm Bill. Another possibility is that farmers achieve economies of scale from clearing pasture. That is, once a farmer has cleared pasture for BCAP crops, it is cost effective for the farmer to clear more pasture for food crops.

V. Robustness

In this section, I conduct further robustness checks on the functional forms.

A. Adding Soil and Climate Characteristics as Controls

Soil and climate characteristics are likely to be determinants in plant location. Additionally, the FSA requires the land enrolled in BCAP to follow certain conservation rules. Since marginal land is encouraged to enroll in BCAP, soil quality inevitably affects changes in land-use after the presence of the BCAP. Table 2.4 shows the regression results after controlling for county-level soil and climate variables during the pre- and mid- periods. The results are consistent with the main regression. Proximity to the plant is associated with conversion of forest to major food crops during the pre- and mid- periods. Table 2.5 shows the regression results after adding county-level soil and climate variables during the mid- and post- periods. The results are consistent with the main regression too. Proximity to the plant is associated with conversion of pasture to BCAP crops and major food crops. However, the magnitudes are larger when soil and climate variables are added, which is unexpected *ex ante*. One possible explanation is that farmer grows BCAP crops on non-marginal land to boost yields and profits because BCAP crops are paid on per ton instead of per acre basis. Table 2.6 shows the correlations between distance to the plant and soil and climate characteristics, as well as the correlations between land-use choices and soil and climate characteristics during the post policy period. The table shows that distance to the plant is highly correlated with the local geographic characteristics; however, land-use choices, especially the BCAP crops, are not highly correlated with the local geographic characteristics.

Table 2.4 Effects of Distance to the Plant on Land-use Change between Pre- and Mid- Policy Periods (First Differencing with Soil and Climate Variables)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
DISTANCE (δ)	0.0000	0.0002	0.0005***	-0.0006***	0.0001	-0.0002
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Soil Moisture	0.0000	0.0029	-0.0049***	-0.0030*	-0.0006	0.0023
	(0.0000)	(0.0017)	(0.0013)	(0.0015)	(0.0007)	(0.0016)
Soil Organic Matter	0.0000	0.0112	-0.0225**	0.0242*	-0.0190***	0.0105
	(0.0000)	(0.0184)	(0.0103)	(0.0138)	(0.0059)	(0.0115)
CACO3	0.0000	0.0166	-0.0144	-0.0386***	0.0195***	0.0103
	(0.0000)	(0.0173)	(0.0098)	(0.0120)	(0.0051)	(0.0122)
Water Erosion Index	0.0000	-0.0016	0.0019***	0.0022**	-0.0002	-0.0007
	(0.0000)	(0.0011)	(0.0006)	(0.0009)	(0.0003)	(0.0006)
Wind Erosion Index	0.0000	0.0021***	-0.0003	-0.0011**	-0.0001	0.0003
	(0.0000)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0004)
Drought	0.0000	0.0081***	-0.0034*	-0.0073***	0.0012	0.0050*
	(0.0000)	(0.0027)	(0.0017)	(0.0016)	(0.0009)	(0.0026)
Flood	0.0000	0.0010	0.0034**	-0.0019	0.0018**	-0.0046**
	(0.0000)	(0.0018)	(0.0014)	(0.0015)	(0.0008)	(0.0017)
Average Temperature	0.0000	8.2407**	-2.8727	-10.5575***	3.9181***	2.9901
	(0.0000)	(2.9902)	(1.9744)	(2.0333)	(0.9928)	(2.7973)
Average Temperature Squared	0.0000	-0.1999**	0.0690	0.2550***	-0.0942***	-0.0723
	(0.0000)	(0.0722)	(0.0477)	(0.0492)	(0.0240)	(0.0675)
Degree Days > 34ºC	0.0000	0.0058	-0.0056*	-0.0043	0.0019	0.0075*
	(0.0000)	(0.0044)	(0.0029)	(0.0042)	(0.0016)	(0.0038)
Constant	0.0000	-85.2822**	29.9928	109.5096***	-40.7587***	-31.0220
	(0.0000)	(31.0586)	(20.4906)	(21.0537)	(10.2964)	(29.0397)
Observations	235,351	235,351	235,351	235,351	235,351	235,351

Note: This table shows the regression results using first-differencing regression with soil and climate controls during the pre- and mid- periods. δ is the slope parameters, which represents the effect of a positive distance to the plant on land-use change between the pre- and mid- policy periods. Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

Table 2.5 Effects of Distance to the Plant on Land-use Change between Mid- and Post- Policy Periods (First Differencing with Soil and Climate Variables)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
DISTANCE (θ)	-0.0014***	0.0018***	-0.0001	-0.0008***	-0.0000	0.0000
	(0.0005)	(0.0006)	(0.0001)	(0.0002)	(0.0000)	(0.0001)
Soil Moisture	0.0034	-0.0070	-0.0003	-0.0039***	0.0000	-0.0005
	(0.0045)	(0.0042)	(0.0006)	(0.0012)	(0.0000)	(0.0005)
Soil Organic Matter	0.1388**	-0.2064***	-0.0051	0.0791***	0.0010	0.0001
	(0.0510)	(0.0567)	(0.0078)	(0.0173)	(0.0006)	(0.0049)
CACO3	-0.1486***	0.2437***	0.0112	-0.0852***	-0.0002	-0.0098**
	(0.0345)	(0.0407)	(0.0079)	(0.0208)	(0.0004)	(0.0038)
Water Erosion Index	-0.0046	0.0060*	-0.0004	0.0032***	-0.0000	-0.0001
	(0.0035)	(0.0034)	(0.0003)	(0.0007)	(0.0000)	(0.0003)
Wind Erosion Index	0.0006	0.0017	-0.0002	-0.0010*	-0.0000	-0.0001
	(0.0013)	(0.0013)	(0.0002)	(0.0005)	(0.0000)	(0.0001)
Drought	0.0020	0.0075	0.0015	-0.0048*	-0.0001	-0.0035***
	(0.0094)	(0.0096)	(0.0014)	(0.0024)	(0.0001)	(0.0008)
Flood	-0.0110*	0.0164**	-0.0010	-0.0085***	-0.0001	0.0020***
	(0.0062)	(0.0070)	(0.0010)	(0.0016)	(0.0001)	(0.0007)
Average Temperature	-14.0908*	33.4182***	1.4067	-17.5381***	-0.0390	-2.0811***
	(7.9136)	(8.5767)	(1.4820)	(3.5132)	(0.0697)	(0.6827)
Average Temperature Squared	0.3409*	-0.8089***	-0.0341	0.4237***	0.0010	0.0503***
	(0.1908)	(0.2069)	(0.0358)	(0.0850)	(0.0017)	(0.0165)
Degree Days > 34ºC	-0.0275**	0.0504***	0.0032	-0.0123**	-0.0002	-0.0037**
	(0.0125)	(0.0141)	(0.0021)	(0.0059)	(0.0002)	(0.0014)
Constant	145.9926*	-346.0658***	-14.5280	181.7937***	0.4041	21.6155***
	(82.2113)	(89.0627)	(15.3838)	(36.4312)	(0.7220)	(7.0785)
Observations	235,351	235,351	235,351	235,351	235,351	235,351

Note: This table shows the regression results using first-differencing regression with soil and climate controls during the mid- and post- periods. θ is the slope parameters, which represents the effect of a positive distance to the plant on land-use change between the mid- and post- policy periods. Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

Table 2.6 Correlations between Distance to Plant and Local Geographic Characteristics and Correlations between Land-use Choices and Local Geographic Characteristics during the Post Policy Period

	Distance to Plant	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
Soil Moisture	-0.1864	-0.0175	-0.0441	-0.1706	0.1688	0.0108	0.0331
Soil Organic Matter	-0.0713	0.0417	0.0766	-0.2156	0.0855	0.0051	0.0218
CACO3	0.4093	-0.0084	0.0039	-0.0725	0.0842	0.0025	-0.0098
Water Erosion Index	-0.2753	-0.0488	-0.1129	0.0004	0.0922	0.0098	-0.0035
Wind Erosion Index	-0.0368	0.009	-0.0038	0.0331	0.0124	-0.0044	0.052
Drought	-0.0798	0.0425	0.0029	-0.0388	0.0331	0.0008	0.0232
Flood	-0.5339	0.0586	0.0373	-0.1269	0.0013	0.0064	0.0391
Average Temperature	-0.2761	0.0256	0.0019	0.0253	-0.0753	-0.0004	0.0319
Degree Days > 34ºC	-0.1638	0.046	0.0588	-0.0309	-0.0702	-0.0019	0.0398

Note: This table shows the correlations between the distance to plant and soil and climate characteristics as well as the correlations between land-use choices and soil and climate characteristics during the post policy period.

B. Extended Sample

Since the BCAP project area includes parcels that are farther away, I also conduct analysis using the extended sample, which includes all sample points within the BCAP boundary of eligibility but excludes sample points that are also in another BCAP project area[1]. Figures 2.8 and 2.9 show land-use trends during the pre- and mid- policy periods respectively. Land-use shows similar trend patterns at different location except pasture in 2007 and 2008. Figures 2.10 and 2.11 plot changes in land-use between the pre- and mid- policy periods and changes in land-use between the mid- and post- policy periods. In general, proximity to the plant is associated with an increase in major food crops and a decrease in forest and pasture before the BCAP. Meanwhile, proximity is associated with an increase in BCAP crops and major food crops and an decrease in pasture in the presence of the BCAP. Land has been mainly transferred from pasture to food crops and BCAP crops after the presence of the BCAP. The graphical results show similar patterns as in the main sample.

Table 2.7 shows land-use changes as a function of distance to the plant between pre- and mid- periods and between mid- and post- periods using the DD. During the presence of the plant but absence of the BCAP subsidies, land has been converted from pasture to food crops. After the presence of the BCAP subsidies, land has been converted from pasture to food crops, BCAP crops, and forest.

[1] The excluded counties which belong to both the BCAP Project Area One and Three are: Boone, Callaway, Cooper, Howard, and Moniteau.

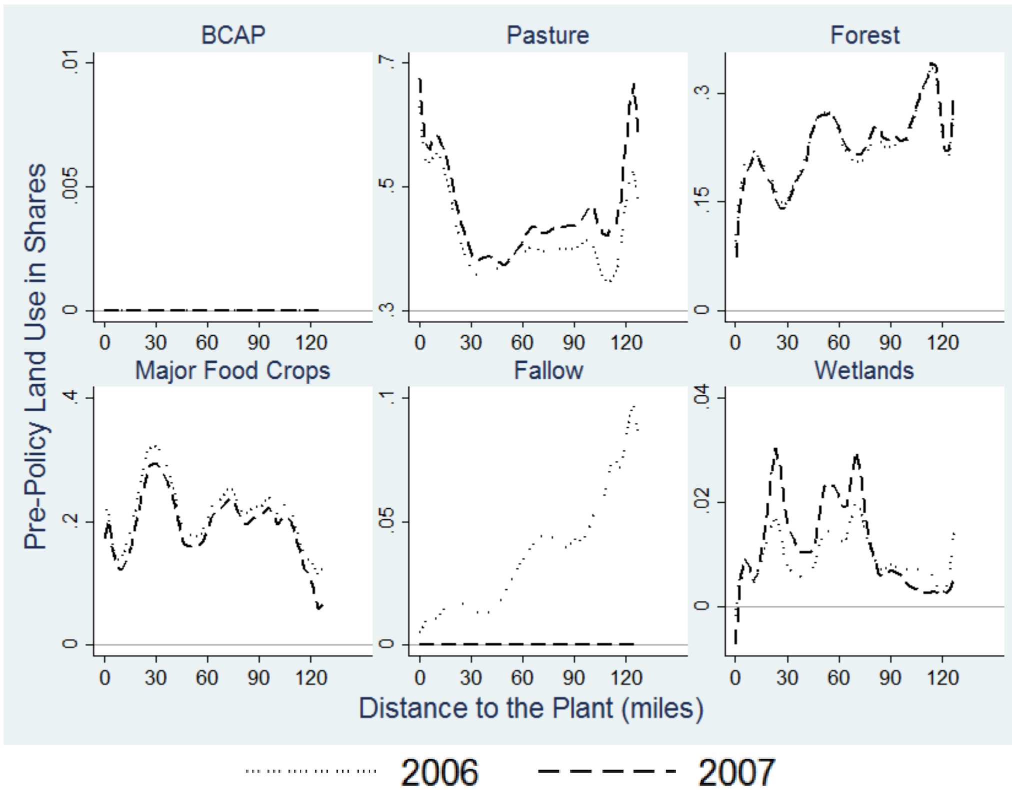

Figure 2.8 Land-use Shares Versus Distance to The Plant During Pre-Policy Years (Extended Sample)

Note: This figure presents land-use shares versus distance to the plant during the pre-policy years using local polynomial regressions. The vertical axes represent land-use shares for each of the six categories and the horizontal axes represent distance to the plant.

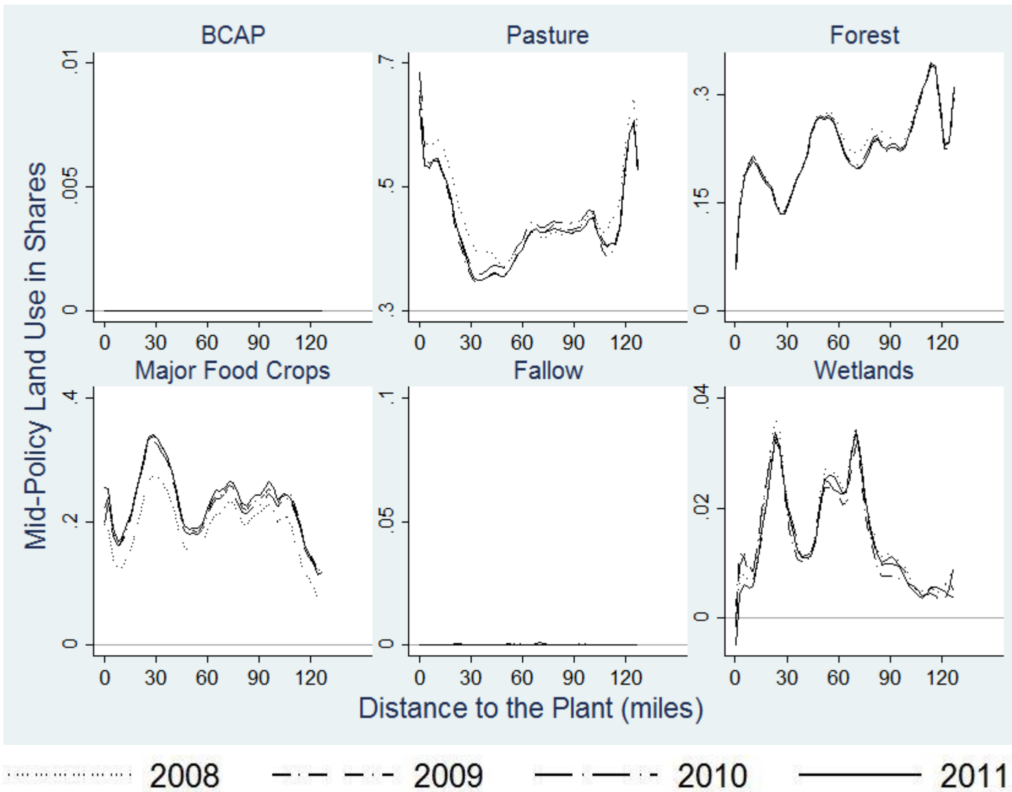

Figure 2.9 Land-use Shares Versus Distance to The Plant During Mid-Policy Years (Extended Sample)

Note: This figure presents land-use shares versus distance to the plant during the mid-policy years using local polynomial regressions. The vertical axes represent land-use shares within their own max-min ranges for each of the six categories and the horizontal axes represent distance to the plant.

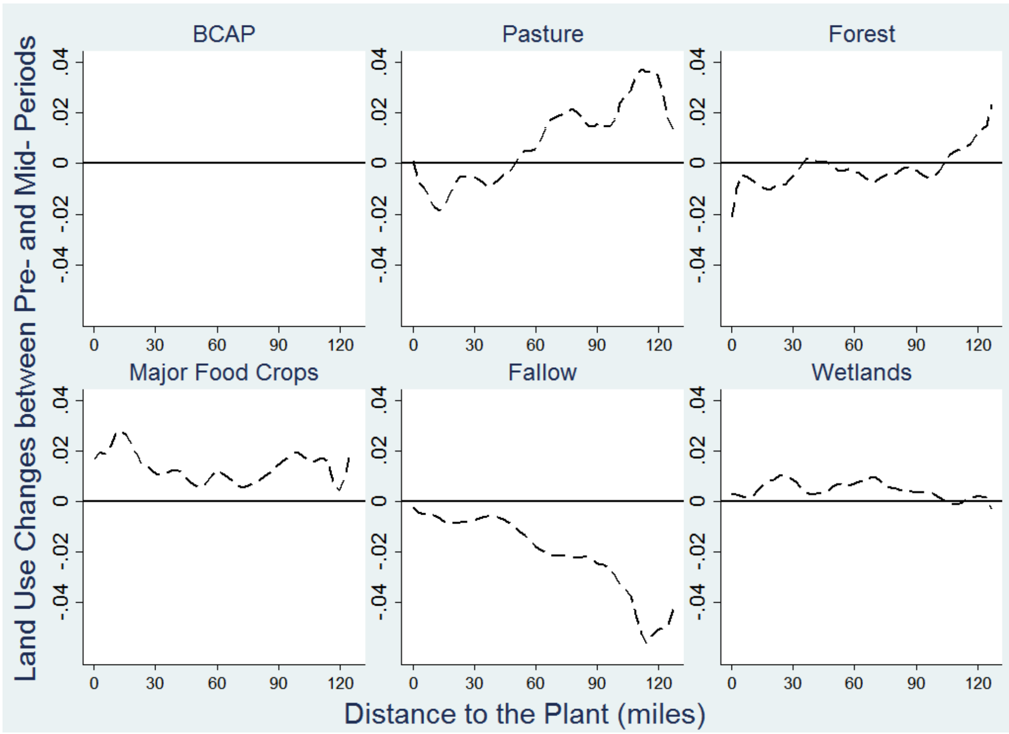

Figure 2.10 Changes in Land-use Shares Versus Distance to The Plant Between Pre- and Mid-Policy Periods (Extended Sample)

Note: This figure presents the changes in land-use shares versus distance to the plant between pre- and mid-policy periods using local polynomial regressions.

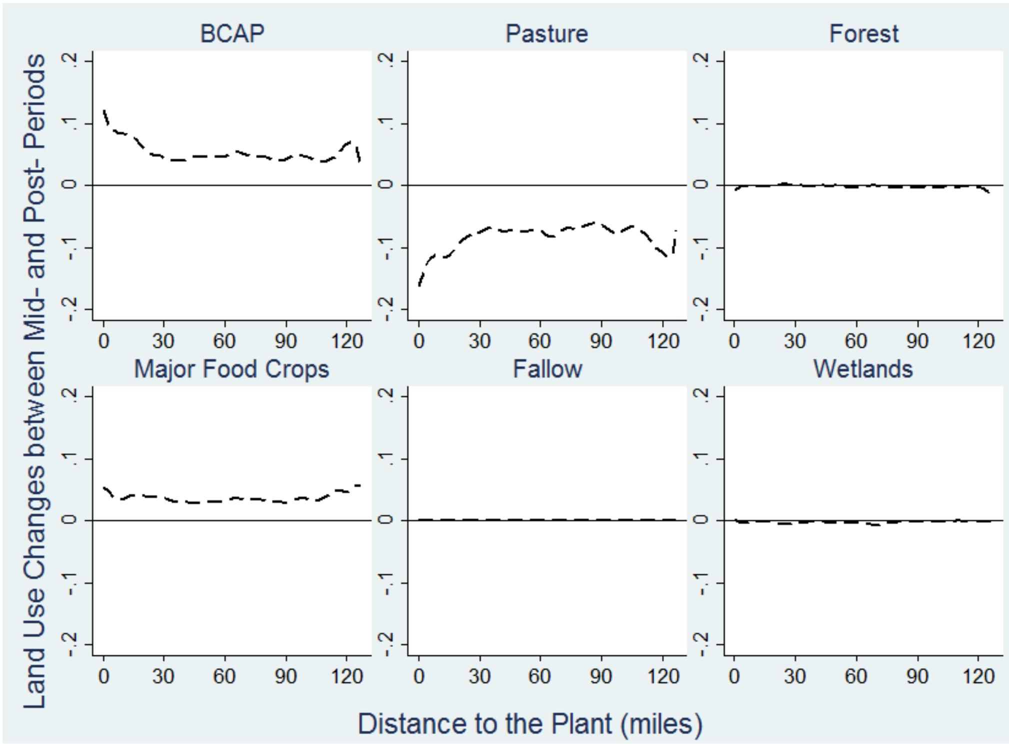

Figure 2.11 Changes in Land-use Shares Versus Distance to The Plant Between Mid- and Post-Policy Periods (Extended Sample)

Note: This figure presents the changes in land-use shares versus distance to the plant between mid- and post-policy periods using local polynomial regressions.

Table 2.8 and 2.9 show land-use changes as a function of distance to the plant between pre- and mid- periods and between mid- and post- periods using DD approach with soil and climate controls. During the presence of the plant but absence of the BCAP subsidies, there is no significant land-use change except wetlands. After the presence of the BCAP subsidies, land has been converted from pasture to food crops, and forest.

Table 2.7 Effects of Distance to the Plant on Land-use Change using the Extended Sample (Fixed Effect)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
MID × DISTANCE (δ)	0.0000	0.0003***	0.0001	0.0000	-0.0002***	-0.0001**
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
POST × DISTANCE (θ)	0.0001	-0.0000	-0.0001**	0.0000	0.0000	0.0000***
	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
MID (β)	-0.0002	-0.0141***	-0.0044	0.0113***	-0.0012	0.0086***
	(0.0002)	(0.0051)	(0.0036)	(0.0038)	(0.0034)	(0.0026)
POST (γ)	0.0569***	-0.0841***	0.0015	0.0306***	0.0002	-0.0048***
	(0.0119)	(0.0135)	(0.0017)	(0.0041)	(0.0001)	(0.0014)
Constant	0.0000	0.4132***	0.2398***	0.2098***	0.0168***	0.0110***
	(0.0018)	(0.0022)	(0.0008)	(0.0013)	(0.0012)	(0.0005)
Observations	2,954,352	2,954,352	2,954,352	2,954,352	2,954,352	2,954,352

Note: This table shows the regression results using fixed effect difference-in-differences regression on the extended sample. δ and θ are the slope parameters, which represent the effects of a positive distance to the plant on land-use change between pre- and mid- policy periods and between mid- and post- policy periods respectively. β and γ are the time trend parameters, which represent the changes between pre- and mid- policy periods and between mid- and post- policy periods at a distance of zero.

Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

Table 2.8 Effects of Distance to the Plant on Land-use Change between Pre- and Mid- Policy Periods using the Extended Sample (First Differencing with Soil and Climate Variables)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
DISTANCE (δ)	0.0000	0.0001	0.0000	0.0000	0.0000	-0.0001*
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Soil Moisture	-0.0000	0.0000	-0.0037***	0.0027*	-0.0016**	0.0017**
	(0.0001)	(0.0017)	(0.0008)	(0.0014)	(0.0007)	(0.0006)
Soil Organic Matter	-0.0002	0.0320***	0.0042	-0.0120*	-0.0147***	-0.0022
	(0.0003)	(0.0103)	(0.0048)	(0.0061)	(0.0048)	(0.0038)
CACO3	-0.0006	-0.0025	-0.0004	-0.0005	0.0007	0.0007
	(0.0006)	(0.0040)	(0.0020)	(0.0036)	(0.0023)	(0.0013)
Water Erosion Index	0.0001	-0.0006	0.0010**	-0.0010	0.0016***	-0.0006**
	(0.0001)	(0.0010)	(0.0004)	(0.0007)	(0.0005)	(0.0003)
Wind Erosion Index	-0.0000	0.0006	-0.0009***	-0.0001	-0.0002	0.0005**
	(0.0000)	(0.0005)	(0.0002)	(0.0004)	(0.0003)	(0.0002)
Drought	-0.0001	0.0041	-0.0001	-0.0002	-0.0025	0.0006
	(0.0001)	(0.0029)	(0.0012)	(0.0021)	(0.0015)	(0.0011)
Flood	0.0001	-0.0012	-0.0006	0.0001	0.0017**	-0.0006
	(0.0001)	(0.0018)	(0.0008)	(0.0013)	(0.0008)	(0.0007)
Average Temperature	-0.0530	-0.5171	-0.0151	0.0912	0.4563***	0.0157
	(0.0468)	(0.3210)	(0.1101)	(0.2194)	(0.1179)	(0.0672)
Average Temperature Squared	0.0013	0.0122	0.0003	-0.0021	-0.0109***	-0.0004
	(0.0011)	(0.0079)	(0.0027)	(0.0054)	(0.0028)	(0.0017)
Degree Days > 34ºC	0.0001	-0.0018	-0.0005	-0.0001	0.0027**	0.0009
	(0.0001)	(0.0026)	(0.0011)	(0.0022)	(0.0011)	(0.0010)
Constant	0.5552	5.3635	0.2660	-0.9764	-4.7661***	-0.1971
	(0.4903)	(3.2802)	(1.1442)	(2.2235)	(1.2366)	(0.6817)
Observations	984,749	984,749	984,749	984,749	984,749	984,749

Note: This table shows the regression results using first differencing regression with soil and climate controls in the extended sample. δ is the slope parameter, which represent the effects of a positive distance to the plant on land-use change between the pre- and mid- policy periods.
Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

Table 2.9 Effects of Distance to the Plant on Land-use Change between Mid- and Post- Policy Periods using the Extended Sample (First Differencing with Soil and Climate Variables)

	BCAP	Pasture	Forest	Major Food Crops	Fallow	Wetlands
DISTANCE (θ)	-0.0003	0.0004**	-0.0001***	-0.0001	-0.0000	0.0000**
	(0.0002)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Soil Moisture	0.0009	-0.0069**	0.0002	0.0050***	-0.0000	-0.0003
	(0.0026)	(0.0031)	(0.0005)	(0.0014)	(0.0000)	(0.0004)
Soil Organic Matter	0.0079	0.0126	-0.0028	-0.0042	0.0001	-0.0026
	(0.0138)	(0.0150)	(0.0027)	(0.0066)	(0.0001)	(0.0023)
CACO3	-0.0009	0.0093	-0.0030**	-0.0034	0.0001	-0.0001
	(0.0053)	(0.0066)	(0.0012)	(0.0034)	(0.0001)	(0.0010)
Water Erosion Index	-0.0013	0.0040***	-0.0004	-0.0017**	0.0000	0.0001
	(0.0012)	(0.0015)	(0.0002)	(0.0007)	(0.0000)	(0.0002)
Wind Erosion Index	-0.0010	0.0002	0.0004***	0.0005	-0.0000	-0.0002
	(0.0008)	(0.0009)	(0.0002)	(0.0005)	(0.0000)	(0.0001)
Drought	0.0060	-0.0083	0.0013	0.0025	-0.0001	-0.0006
	(0.0049)	(0.0059)	(0.0008)	(0.0028)	(0.0001)	(0.0008)
Flood	0.0004	-0.0008	-0.0012**	-0.0008	0.0000	0.0008*
	(0.0037)	(0.0040)	(0.0005)	(0.0016)	(0.0000)	(0.0004)
Average Temperature	-1.3917***	2.2093***	-0.1017*	-0.5334***	0.0018	-0.0458
	(0.3553)	(0.3899)	(0.0553)	(0.1898)	(0.0031)	(0.0502)
Average Temperature Squared	0.0341***	-0.0544***	0.0025*	0.0132***	-0.0000	0.0011
	(0.0087)	(0.0095)	(0.0014)	(0.0046)	(0.0001)	(0.0012)
Degree Days > 34ºC	-0.0021	0.0099**	-0.0011	-0.0044**	-0.0000	-0.0002
	(0.0037)	(0.0042)	(0.0008)	(0.0020)	(0.0000)	(0.0006)
Constant	14.1987***	-22.4506***	1.0418*	5.3767***	-0.0171	0.4764
	(3.6349)	(3.9998)	(0.5614)	(1.9505)	(0.0312)	(0.5126)
Observations	984,779	984,779	984,779	984,779	984,779	984,779

Note: This table shows the regression results using first differencing regression with soil and climate controls in the extended sample. θ is the slope parameter, which represent the effects of a positive distance to the plant on land-use change between mid- and post- policy periods.
Standard errors are clustered by county and shown in parentheses. *** indicates significant at 1 percent level; ** indicates significant at 5 percent level; * indicates significant at 10 percent level.

VI. Conclusions and Discussions

In this paper, to study biomass promotion and deforestation prevention, I empirically estimate land-use changes induced by the demand for bioenergy crops in a quasi-experiment. Using a difference-in-differences approach, I find that the opening of a large cellulosic biomass conversion plant in central Missouri shifts the local demand for food crop residues upward, causing land-use conversion from forest and pasture to major food crops near the plant. I also find that the offering of the BCAP subsidies induces the demand for native grasses in the same area, causing land conversion from pasture to BCAP crops and major food crops.

Most of the land-use changes identified in this study make sense. For example, under BCAP conditions, farmers have the incentive to grow bioenergy crops on the other lands, such as pasture. However, farmers did not convert forest to food crops, which is surprising, given the high food crop prices during the study period. One possible reason is that farmers are forward-looking and expecting crop residues to become eligible for BCAP subsidies soon.

This study has two limitations due to data availability. First, it focuses on the short-term effectiveness of biomass promotion incentives. Therefore, it does not address the "crowding out" issue raised by Song, Zhao, and Swinton (2011) in the long run. Second, it does not address whether land-use in the Conservation Reserve Program, Grassland Reserve Program, and Wetland Reserve Program, which are close substitutes for the BCAP, is affected by the demand for biomass crops.

Despite these limitations, the joint results have significant implications in guiding environmentally friendly biomass policy. First, the forms and magnitudes of external incentives matter in biomass promotion. While the plant alone only induces a small amount of bioenergy crop supply, the plant combined with BCAP induce a large supply, highlighting the importance of subsidies in promoting a new biomass market. The plant opening and the BCAP subsidies together successfully solve the chicken-and-egg challenge. Second, deforestation can be discouraged if regulation is integrated into the subsidy. Unrestricted biomass promotion indeed risks encouraging the landowner to convert forest to biomass, as evidenced by deforestation in the presence of the plant alone. However, when restrictions, such as those in BCAP, which exclude converted forest for eligibility, are provided, deforestation is deterred, highlighting the role of regulation in controlling undesirable land-use changes. It will be interesting to evaluate other forms of biomass-promotion policies in preventing deforestation in the future. Third, this study is informative to policy makers who intend to spur bioenergy crop production at different policy levels. My post-policy evaluation of biomass promotion at pilot scale suggest that when BCAP extends to national level, the RFS may be met, though general equilibrium effects such as increased food crop prices may undermine the effects of the BCAP-type subsidies. In addition, by carefully restricting eligibility of land-use for bioenergy crops, unexpected effects of demand for bioenergy crops on land-use such as deforestation can be minimized. Altogether, I provide evidence that a robust subsidy can indeed kill two birds by one stone.

APPENDIX

APPENDIX: Non-Agricultural Land Cover Definitions

Pasture/Hay: "Areas of grasses, legumes, or grass-legume mixtures planted for the production of seed or hay crops, typically on a perennial cycle."

Deciduous Forest: "Areas dominated by trees where 75 percent or more of the tree species shed foliage simultaneously in response to seasonal change."

Pasture/Grass: Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing.

Woody Wetlands: "Areas where forest or shrubland vegetation accounts for greater than 20 percent of vegetative cover and the soil or substrate is periodically saturated with or covered with water."

Fallow: "Areas used for the production of crops that do not exhibit visable vegetation as a result of being tilled in a management practice that incorporates prescribed alternation between cropping and tillage."

Grassland/Herbaceous: "Areas dominated by upland grasses and forbs. In rare cases, herbaceous cover is less than 25 percent, but exceeds the combined cover of the woody species present. These areas are not subject to intensive management, but they are often utilized for grazing."

Barren: "Areas characterized by bare rock, gravel, sand, silt, clay, or other earthen material, with little or no "green" vegetation present regardless of its inherent ability to support life. Vegetation, if present, is more widely spaced and scrubby than that in the "green" vegetated categories; lichen cover may be extensive."

Mixed Forest: “Areas dominated by trees generally greater than 5 meters tall, and greater than 20 percent of total vegetation cover. Neither deciduous nor evergreen species are greater than 75 percent of total tree cover.”

Evergreen Forest: “Areas dominated by trees generally greater than 5 meters tall, and greater than 20 percent of total vegetation cover. More than 75 percent of the tree species maintain their leaves all year. Canopy is never without green foliage.”

Herbaceous Wetlands: “Areas where forest or shrubland vegetation accounts for greater than 20 percent of vegetative cover and the soil or substrate is periodically saturated with or covered with water.”

Source: NLCD 2001 Land Cover Class Definition. http://www.epa.gov/mrlc/definitions.html

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Conclusions

This dissertation studies the impacts of climate change and energy policy on U.S. agriculture, in terms of land-use choice, land-use change, and the underlying mechanisms driven these changes.

In the first chapter, I comprehensively investigate the impacts of climate change on agricultural yields for almost two-dozen field crops widely cultivated in the contiguous United States, as well as on land-use changes and farmland values with a joint structural econometric model of farmland value and land-use choice. I find that drought and cold have the most significant impacts on U.S. agriculture, implying that wetter and warming climate associated with less drought and cold may benefit U.S. agriculture. Furthermore, adaptation via selectively modifying crop biological and physiological attributes (e.g., root depth and stomata density) is likely to reinforce the beneficial impacts of warmer and wetter climate.

In the second chapter, I assess the land-use changes associated with the establishment of large cellulosic biomass processing plant in Central Missouri and the following presence of the Biomass Crop Assistance Program (BCAP) which provides financial aids to native bioenergy grasses growers near the plant. In a quasi-experimental framework, I find that the plant alone induces land conversion from forest and pasture to major food crops and the BCAP induces land switching from pasture to major food crops and native bioenergy grasses. By explicitly excluding forest land for BCAP subsidies, the program effectively discourages deforestation, which is one of the major concerns in biomass and bioenergy development.

My dissertation research provides empirical supports for adaptation to climate change in agriculture due to the great room and economic values associated with adaptation. It also sheds light on the bright side of biomass market establishment and development. The results may be used by policy makers, agricultural investors, and university extensions in assisting farmers to survive and sustain U.S. agriculture under a rapidly changing environment.