# ADAPTATION TO CLIMATE CHANGE WITH CROP INSURANCE: CASE OF THE US FEDERAL CROP INSURANCE (1990-2015)

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## ABSTRACT

The central question of studies of economic impacts of climate change is adaptation of economic agents. In US agricultural market, it is not known if and how farmers are making decisions to manage risks from climate change with current tools available. How farmers allocate their resources to manage risk under changing risk level of production is not well understood in empirical setting. In this study, I identify the effects of weather shocks on the United States federal crop insurance demand, using crop insurance data, corn production data, weather data, and climate opinion data. The data spans every county in the US from 1990 to 2015.

I find that farmers on the eastern side of the 100$^{th}$ meridian line in the US start adapting to climate change by enrolling more corn farmland into crop insurance programs following the period of heat shocks. More specifically, a 1,000-unit of increase in extreme degree days the share of insured land ratio of the next year by 0.02 on average. The results are however observed only in the second period (2003-2015) of the data for the counties in states on the eastern side of the 100$^{th}$ meridian line in the US. One hypothesis that I proposed in this study is that the underlying risk attitude has changed due to changing beliefs about climate distributions. I test the hypothesis of production risk attitude, denoted in this study as proportion of population who believed in global warming to be one explanatory variable with cross-sectional data from the year 2014, regressing it on changes in insured land ratio. I find that the higher share of population who believe in global warming in a county is correlated with higher changes in insured land ratio. This confirms our hypothesis that farmers start adapting to climate change using crop insurance, however, only starting in the second period of the study. The paper contributes to the literature on economic impacts of climate change and crop insurance demand.

# BIOGRAPHICAL SKETCH

Ithipong "Billy" Assaranurak is originally from Thailand. He came to the US in 2008 with the mission to understand agricultural market in Thailand and in the world in pursuit of improving livelihood of farmers in Thailand and other countries. His initial focus was on improving efficiency on the supply side of the rice market in Asia with biological research. Ithipong has learned many cutting-edge technologies in crop research and have had many opportunities to see various sides of agricultural market. Yet his passion and the drive to understand what truly affects welfare of farmers and how the market works lead him to do double majors in crop sciences and agricultural economics. With many great teachers he has had at the University of Illinois at Urbana-Champaign, he took various courses in agricultural economics and other-related fields that later instilled him passion to pursue higher education in Applied Economics and Management at Cornell. Here, he has had many great teachers and role models in applied economics. Now that he is graduating from the program, he his pursuit of knowledge and truth are yet to finish, and he is now excited to go out and actively contributes to the world, especially in developing countries.

# ACKNOWLEDGEMENT

I would like to dedicate this thesis for my parents for their unyielding support, friends, relatives, mentors, and everyone around me. Their contributions are sincerely appreciated and gratefully acknowledged. I would like to express their deep appreciation and indebtedness particularly to the followings:

To Nancy, for always giving unconditional support and unprecedented encouragement for her students to explore possibilities in work and research.

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To all the professors at Cornell who have been so inspirational for me to reach apex of truth and knowledge.

To all my life-long friends, Poom, Nop, and Pol who always shared their morally and emotionally support from day 1. Thank you for supporting me since I left Thailand to pursue my education in the States.

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For

Mom, Dad, Pook and Ming

# CHAPTER 1 INTRODUCTION

The discussion of climate change has started in the late 1980s and continued into the present day, and yet its effects on the economy is still not fully comprehended. As climate change is expected to have large impacts on the agricultural sector, many studies have developed methods to quantify this impact and study various mechanisms climate change could affect the sector. In this study, I attempt to quantify effects of climate change on crop insurance demand, using the US federal crop insurance data, corn production data, and weather data. I examine how farmers respond to weather shocks with crop insurance and check the underlying assumptions on beliefs about weather shocks across regions and time.

The history of the US federal crop insurance and its organization, the Federal Crop Insurance Corporation, is long-standing, starting in 1938 after the long-lasting Dust Bowl catastrophe (Shields, 2015). Since then, the program has grown in size and reached 256 million acres of coverage with $78 billion in liability in 2010 (Coble et al., 2013). The crop insurance program does not only reduce risks of the producers, but also provides a fertile field to study behaviors of economic agents with natural experiments. The study of factors that influence crop insurance demand is of interest to both policymakers and economists and has been under investigation for a long time. However, none has examined the effects of climate change on crop insurance demand. In this paper, I attempt to fill this gap using weather data, crop insurance, corn production, and climate opinion data to identify responses of US farmers on insurance demand to weather shocks over region and over time. Data spans from 1990-2015 across the country. Understanding how this underlying assumption affects crop insurance demand will be important to policy making for crop insurance policies and also for production decision making by farmers.

## 1.1 Climate Change and the US Farmers' Adaptation

The degree of adaptation of US farmers to climate change is puzzling. First, despite the wide variety of tools for farmers to use to cope with increasing production risk from weather, the process of how farmers make decisions on using these tools to cope with increasing risk is still not fully understood[1]. Specifically, despite the levels of loss that increasing risk from climate change could bring, the importance of recent weather shocks on the demand for crop insurance has not been fully identified. Understanding this effect of climate change on crop insurance demand will be crucial.

*Figure 1-1: Average Maximum Temperature Trends in June in the US (Source: National Oceanic and Atmospheric Administration (NOAA))*

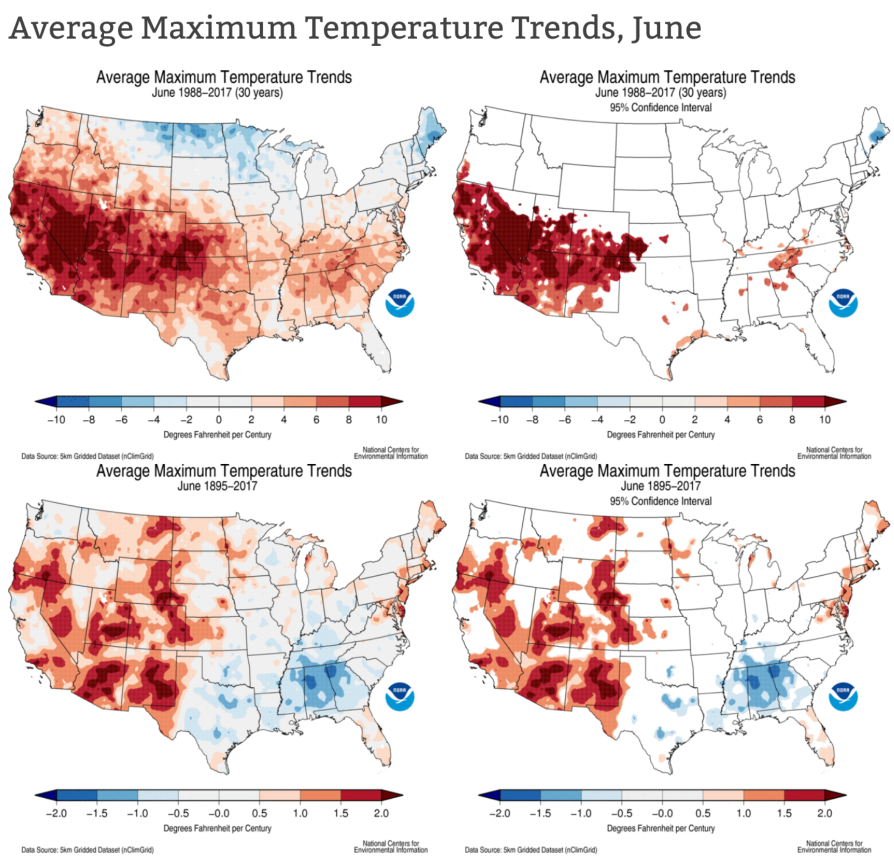



Figure 1-1 illustrates the positive trend in average maximum temperature for the month of June and certain parts of the country are becoming hotter than before. Learning of these climatic changes requires that farmers learn from their own experience or from others (Hanna, Mullainathan, & Schwartzstein, 2014). Wide variety of mechanisms are available for farmers to use to deal with risk

[1] The terms, climate and weather, will be used interchangeably throughout the thesis. The term climate represents distribution of weather events in a region, while weather refers to a realization of climate distribution.

in the market, including governments' farm programs, crop switching, exit from agriculture, irrigation use, hedging in the futures market, investing in other non-farm activities, and a decrease in farm investment. Examples of the US government's farm program include crop insurance program, price subsidy, and disaster payments.

## 1.2 The US Federal Crop Insurance Market

The US federal crop insurance market has been available to the US farmers since 1938, and the adoption has continued to grow over time; however, the factors that drive growth in crop insurance demand are still puzzling.

I investigate the effects of climate shocks on crop insurance demand. Crop insurance in the US sees strong growth in adoption from the year 1990-2015. How much of this adoption is accounted for by climatic factors? Insurance adoption in the US Farmers is driven by (1) policies that mandate participation, (2) amount of subsidy, and (3) farmers' financial risks. With the co-existing public discussion and concern about climate change during the same period, I want to test whether and how much concerns about climate change drove crop insurance adoption in the US.

The US federal crop insurance program is one of the most developed crop insurance programs in the globe. Understanding how to attain optimal crop insurance pricing that will maximize program participation will allow the government to set the price that maximizes utility to the market. Farmers constitute the demand side of the crop insurance market. Crop insurance helps in protection from loss damage. Farmers benefit from this program. The government's spending on disaster payment also decreases with the crop insurance program.

Effects of climate change on crop insurance demand that I consider in this study are two levels: (1) direct effects of climate change on crop insurance demand and (2) belief effects about climate change on crop insurance demand. By identifying this relationship between farmers' responses to weather shocks in crop insurance demand, I solve the problem by identifying how people perceive weather shocks and use crop insurance to deal with their increasingly risky environment. With the consideration of cutting subsidy for crop insurance, understanding this relationship between farmers' risk management using crop insurance and weather shocks will be crucial to the budget consideration as crop insurance can help improve the welfare of the farmers.

In this paper, I have shown that despite the difficulties in quantifying whether farmers recognize the subtle changes in climate, the results indicate that farmers still respond to weather shocks by enrolling more land into crop insurance programs in the second half period of the study. The novel contribution of this paper is the following: identification of adaptation using Bayesian updating model with crop insurance demand, out-of-sample prediction with distributed lag panel model, and model of how extreme weather events affect farmers' priors about climate change and farmers' adaptation strategies.

The rest of the thesis will be presented as follows. In Chapter 2, I review literature in crop insurance demand and economic impacts of climate change. In Chapter 3, I give the conceptual framework that will be used to analyze the concepts of weather shocks to crop insurance demand particularly under ambiguous information on underlying risk assumptions based on the expected utility framework. In Chapter 4, I give summary of data that I use in this study in the US crop insurance context from 1990 to 2015. In Chapter 5, I show the empirical approach that I use to identify the weather shock effects on crop insurance demand in a panel setting. In Chapter 6, I explain analysis with highlights of results. In Chapter 7, I discuss the results from Chapter 6 and explain how this fits into a larger picture and contributes to the literature. In Chapter 8, I give conclusion of this study and what it contributes as well as future lines of work.

# CHAPTER 2 LITERATURE REVIEW

Because this thesis consists of an examination of farmers' behaviors in purchasing crop insurance in response to weather shocks, it is crucial to examine literature in the fields of crop insurance and economic impacts of climate change. Both fields of literature are extensive, and yet the amount of literature that unifies both fields is still scarce.

## 2.1. Studies on Economic Impacts of Climate in the Economy

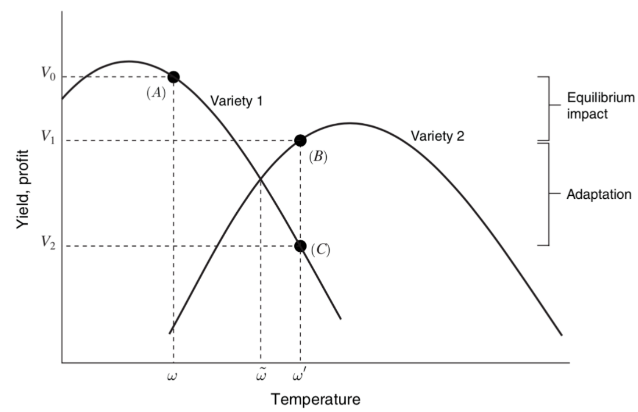
Climate fluctuations have been known to be associated with levels of growth and economic development. Dell, Jones, and Olken (2014) explains that to examine in a cross-sectional setting, differences in climate cannot be used to explain changes in economic institutions, yet random fluctuations in panel models can be used to causally identify effects of weather on the economy. In their other paper, they find in panel setting that weather shocks can affect economic growth and production, especially in hot and poor countries where agriculture is one of the major economic sectors (Dell, Jones, and Olken, 2012). The paper reviewed methods and data types used in the study of climate effects in the economy. Climate change particularly has been known to affect agricultural sector and can have large implications to the sector (Auffhammer and Schlenker, 2014; Dell et al., 2014; Felkner, Tazhibayeva, and Townsend, 2009; Hsiang, 2016)

### 2.1.1 Methods to Study Economic Impacts of Climate Change

The studies of the economic impacts of climate change in agriculture started with biophysical models (Kaiser et al., 1993). The most crucial assumption of this model is that farmers do not assume any cost in adaptation and thus, farmers can easily adapt to environmental changes using methods such as varietal switches.

Mendelsohn, Nordhaus, and Shaw (1994) were the first to use the Ricardian approach in estimating economic impacts of climate change on the agricultural sector, and many other papers have followed this approach (Schlenker, Michael Hanemann, and Fisher (2005), Schlenker, Hanemann, and Fisher (2006), Deschênes and Greenstone (2007), Chen and Dall'Erba (2017)). It is based on the regression of land values on historical climate data, using cross-sectional data and estimating the differences across the region to estimate the impact of random occurrences of weather shocks on economic activities in a given region. This approach accounts for adaptation by farmers without behavioral data. The assumption is that if I assume that land price reflects discounted future profit, I can assess adaptation from changes in profits varying over climate. For example, farmland rent would reflect farmers' adaptation. The data are mostly in cross-sectional format. However, its major problem is omitted variable bias.

*Figure 2-1: Productivity of two different corn varieties under different temperature levels (Source: Burke and Emerick 2016)*




Deschênes and Greenstone (2007), henceforth DG, was the first to use farm profit model, which assumes that farmers have already priced in adaptation and climate change information into the model. The model is illustrated in Figure 2.1. Panel approach uses variations over time to compare a specific area's outcomes under hotter versus cooler conditions. Examples of papers that use this approach are DG 2007, 2011, Barreca et al., 2016; Dell et al., 2012; W. Schlenker and Roberts, 2009. However, the problem with this approach is that the average climate could be correlated with other time-invariant factors unobserved to the econometrician. Short-run variation in climate within a given area (weather) is plausibly random and thus better identifies the effect of changes in climate variables on economic outcomes.

Panel data is useful in accounting for time factors and heterogeneity in the data. The method used to analyze panel data exploits weather shocks while using data over time and spatial units. It usually includes fixed effects. For example, spatial fixed effects control for time-unvarying characteristics in that spatial area. The method usually solves issues of omitted variable bias. Particularly for studies that involve agricultural land productivity, they include the effects of soil characteristics. The other common fixed effect used is year fixed effects, which account for time-varying characteristics.

### 2.1.2 Economics of Climate Change and Adaptation

One issue that remains unresolved and remains central to research in the area of economic effects of climate change is the adaptation of economic agents. In the case of agriculture, it is still unclear what methods farmers use or how farmers adapt to this phenomenon.

Major papers include those by Burke and Emerick (2016), Hornbeck (2012) and Kelly, Kolstad, and Mitchell (2005). An example of a major event that has a long-term negative effect on the US agriculture and requires adaptation from the farmers is the Dust Bowl event in the 1930s. The Dust Bowl was the catastrophic event in which large dust storms swept more than 75% of the topsoil from the Great Plains land, and the economic damage was so large that many families left the unfertile soil and migrated further to the West (Hornbeck, 2012). The event left a long-term impact on the farm productivity, the industry, and subsequently the farmland price. Risk attitude is nonetheless an important underlying concept for economic decision (Hansen, 2017).

## 2.2 Economic Literature on Crop Insurance

Crop insurance has been a topic of interest to researchers who study risks and production decisions in the farm sector. With the US crop insurance program started in 1938, many papers have studied various facets of the US crop insurance program.

### 2.2.1 History of the US Federal Crop Insurance Program

To put the policy effects in perspective, the following policy enactments can be outlined. In the year 1938, the US government enacted the Federal Crop Insurance Act of 1938 to cope with weak economic conditions in the economy during the Great Depression and particularly to alleviate adverse effects in the farm sector due to the Great Dust Bowl. However, the participation remained low in the first 40 years of the program, partly because of competition with free disaster coverage. The Federal Crop Insurance Act of 1980 was enacted, and more subsidy was issued to the program. Another Federal Crop Insurance Act was enacted in 1994; the Act mandated that growers must participate in the crop insurance program to receive disaster payments from the government. Since then, the participation in the program has been increasing, except for the slight drop in the period of 1995-1997 when the government decoupled disaster payment from the insurance program [Figure 2.1]. Several other policies have been enacted since then, affecting the demand of crop insurance among the US farmers.

*Figure 2-2: Adoption (Insured Land Ratio) Trend for Corn Insurance*

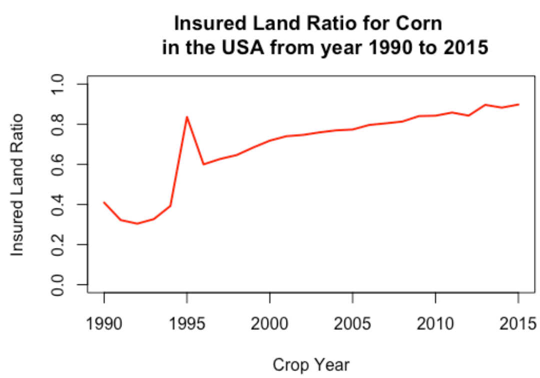


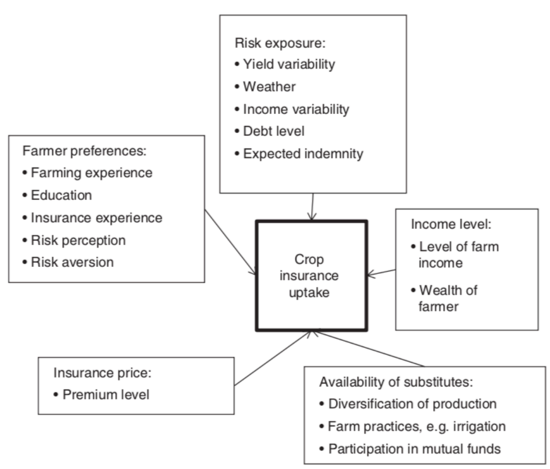

Figure 2-2 shows trends in the crop insurance demand, which has increased continuously from year 1996 onwards. However, variations by counties are not well-explained in this figure. The crop insurance program has now been offered for more than 80 crops. Sizes of insurance programs for corn, wheat, and soybean, however, comprise more than 75% of the total crop insurance purchases (Shields, 2015). For corn insurance, there are now 4 types of policies and coverage levels from 50% to 85%. These different types of crop insurance policies offer important aspects of how farmers consider insurance take-up.

### 2.2.2 Crop Insurance Demand

Crop insurance demand in the US has been extensively studied and yields interesting results. Coble, Knight, Pope, and Williams (1996) were one of the first group of researchers that attempt to model crop insurance demand in the US market with panel data.

Crop insurance experience in other countries has gained traction. The determinants vary over financial factors and risks in production. Factors that determine crop insurance use include (1) farmer's utility functions, (2) farmer's income, (3) premium, (4) subjective frequency distribution of his future income, and (5) change in the frequency distribution after buying crop insurance (Niewuwoudt and Bullock, 1985). Wąs and Kobus (2018) explains that the standard crop insurance literature assumes that risk exposure (yield variability, weather, income variability, debt level, expected indemnity, and farm size), income level (level of farm income and wealth of farmers), farmer preferences (farming experience, education, insurance experience, risk perception, and risk aversion), availability of substitutes (diversification of production, farm practices, and participation in mutual funds), and price (level of premium) can affect crop insurance demand (Figure 2.3). Weather variables in this study only affect crop insurance take-up through risk exposure and farmer preferences. They affect insurance experience, risk perception (through beliefs of climate risks), yield variability, and income variability. Thus, through these channels, I expect to pick up the effects of weather on crop insurance demand variations.

*Figure 2-3: Determinants of Crop Insurance Demand (Source: Wąs and Kobus (2018))*



### 2.2.3 Climate Change and Crop Insurance Demand

None of the literature that I am aware of has specifically examined the effects of climate change on crop insurance demand yet. The closest resembling paper is that of O'Donoghue and Tulman (2016), which considers the effects of yield shocks on insurance elasticity. The other paper by Annan and Schlenker (2015) also similarly considers the effects of climate shocks on crop insurance demand in the US. Nonetheless, both studies did not consider the factors of changing distributions from climate change and growers' perceived risks about the environment.

Framework to study effects of climate change on farmers' adaptation mechanisms with incorporations of belief effects has been established in the paper by Burke and Emerick (2016). Farmers' wealth has heterogeneous effects on crop insurance demand. Farmers who are more at risk of climate shocks will buy more insurance. Weather shocks will signal the more risk in production and the changes that farmers will have to adapt to. While farmers' expected return and risk reduction improve under a crop insurance policy, it is puzzling why participation in crop insurance is not yet saturated despite its benefits. The problem can be explained with adverse selection. Farmers might choose to insure only on lands that are at risk and not insure those lands that have higher yield potential.

# CHAPTER 3 THEORETICAL MODEL

Farmers are the decision makers in the economy. In this paper, I use the expected utility model to explain the economic behaviors of farmers regarding crop insurance and weather risks. I also assume that they are profit maximizers with incomplete information and that they update their beliefs in a Bayesian manner. Climate change phenomenon represents additional risk and uncertainty in agricultural production. Two effects that it has are changes to the climate distribution, including climate mean and variance, and degree of speculation that it causes farmers to estimate the actual changes in the climate distribution on their farmland, assuming that farmers do not know the exact changes this phenomenon causes. Because I am interested in the effects of climate on crop insurance demand, considering the mechanisms through which weather (climate realization) can affect insurance demand will be important to the study.

Weather directly determines yield through the amount of sunlight, which can be captured partially through heat, rain, and humidity. In this study, I use the two variables available in my dataset namely, heat and precipitation, to capture weather realizations of global climate. Both variables not only capture the physical effects of weather onto yield, but also to the characteristics of events that affect farmers' beliefs about production risks and thus their decision making on crop insurance.

## 3.1 Expected Utility Model

Utility maximization is the underlying theoretical structure in many economic models involving decision making under uncertainty. In this study, I determine insurance choices that a farmer will make through analyzing his utility function with respect to his expected income. In the market, farmers can be risk loving, risk neutral, or risk averse. In the case that farmers are risk loving, they will not buy crop insurance regardless of the price of the insurance. In contrast, if farmers are risk averse, their decision on buying crop insurance will depend on the premium of insurance and the expected utility of the event. It can be analyzed as the following.

Farmers are utility maximizers. When farmers are risk averse, their utility function is concave. For example, for risk-averse farmers, one form of utility functions can be represented as:

$$EU(y) = \ln(y)$$

where $EU(y)$ represents expected utility and $y$ represents income. The logarithmic function indicates a concave form of the expected utility model.

The expected utility model for income that I use is in the following form:

$$EU(y) = Ey - RVar(y)$$

where $EU(y)$ stands for expected utility of farmers with income $y$, $Ey$ is expected income, and $Var(y)$ is the variance of the income $y$. $R$ is a constant with a value from 0 to 1. This form indicates that farmers' expected utility is a function of expected income and variance of income. Farmers' expected utility of income $y$ rises with $Ey$, but decreases as variance of income $y$ increases.

To establish relationships between farmers' income and climate conditions, I denote that farmers plan for output $x$ with cost $cx$ for price $c$ and realized output $\kappa x$. $\kappa$ is a random variable with mean $\bar{\kappa}(C)$ and variance $\mathrm{V}(C)$, where $C$ denotes climate change conditions.

As I am interested in the channels of effects of climate conditions on expected income, I define the direct effect as the degree in which weather directly affects insurance decisions and denote it as dependence of $\bar{\kappa}(C)$ on $C$. Next, I also would like to clarify the effects of beliefs in climate conditions on insurance decisions. I denote the belief effect as the dependence of $\mathrm{V(C)}$ on $C$. respectively. However, whether $C$ increases or decreases $\bar{\kappa}$ and $\mathrm{V}$ depends on the nature of climate change. A corner solution for maximal output $\bar{x}$ is applied for fixed input, such as land.

Farmers have options to buy crop insurance at cost $T$, and it reduces revenue impact of the random $\kappa$ from $Var(y)$ to $(1-\sigma)Var(y)$ where $\sigma \in [0,1]$. With crop insurance, $\mathrm{V}(C)$ only increases in C.

With this framework, farmers' income will be affected with changes in weather in 2 ways. First, farmers' mean income will be affected with the changes in mean of climate. Second, with farmers' options to purchase crop insurance to reduce impact of risk in production on income, farmers' subjective beliefs about climate will likely affect this decision.

**Our model assumes the following:**

Farmers' risk preferences are constant with the form of absolute risk aversion:

$$\lambda = -\frac{U''(y)}{U'(y)}$$

1. I assume that this form of risk preferences is constant through time and across space. Discussion of the case where this is not true is highlighted in the appendix.
2. Relationships between productivity and climate change variables are defined as direct effects, which defines dependence of $\bar{\kappa}(C)$ on $C$. This denotes how productivity, $\bar{\kappa}$, depends on $C$.
3. Relationships between perceived variability and climate change variables are denoted as belief effects, which defines dependence of $V(C)$ on $C$.

Here, $C$ denotes climate, which stands for climate change variables. In our model, $C$ is defined as the changes in climate variables in year $t$. With this particular set of data, I define $C$, climate change variables, as Growing Degree Days 30-50 °C (henceforth GDD30-50). It is defined as the amount of heat in climate from 30 °C to 50 °C during a defined period in a particular crop growing season. This GDD30-50 will affect both mean and variance of the climate change variables. The other climate change variable used in this study are Growing Degree Days 10-30 °C (henceforth GDD10-30), which defines optimal growing temperature range for plants. Both of these variables constitute climate variables and indicate both mean and variance of climate conditions, as the increase in GDD30-50 indicates more climate variance and, all else constant, higher mean of climate.

With the expected utility of the income of the farmer in the absence of crop insurance takes the form of:

$$EU(x) = (\bar{\kappa}(C) - c)x - Rx^2V(C)$$

And the expected utility of the income of a producer who subscribes to crop insurance takes the form of:

$$EU(x_{ins}) = \bar{\kappa}(C)x - cx - T - R(x^2(1-\sigma)V(C))$$

Without crop insurance, the expected utility that maximizes output level of the farmer is:

$$EU(y^*) = \frac{(\kappa(C) - c)^2}{4RV(C)}$$

With crop insurance, the expected utility that maximizes output level of the farmer is:

$$EU(y_{ins}^*) = \frac{EU(y^*)}{1 - \sigma} - T$$

Farmers' maximal willingness to pay for crop insurance is:

$$T^* = \frac{\sigma}{1 - \sigma} \frac{(\bar{\kappa}(C) - c)^2}{4RV(C)}$$

Our expectations on the insurance decisions of farmers in each county are the following:

Farmers' maximum willingness to pay for crop insurance will increase when:

$$\frac{\frac{d\kappa(C)}{dC}}{\frac{dV(C)}{dC}} > \frac{(\bar{\kappa}(C) - c)}{2V(C)}$$

Such conditions can be met in counties where $\frac{d\kappa(C)}{dC}$ is positive and is larger than $\frac{dV(C)}{dC}$ because $\frac{dV(C)}{dC}$ is always positive. This is true in the states that benefit from climate change, such as states that have low mean temperature in the beginning and thus low $\kappa$. However, $\kappa$ increases over C, and V(C) increases under C as well. This can be captured through GDD30-50 variables.

Farmers' maximum willingness to pay decreases when:

$$\frac{\frac{d\kappa(C)}{dC}}{\frac{dV(C)}{dC}} < \frac{(\bar{\kappa}(C) - c)}{2V(C)}$$

Possible states include Texas. This signifies if farmers live in the states where temperature is already high and if farmers benefit from increasing temperature.

### 3.2 Dynamic Model

As the model presented above represents a static model, now I would like to present a dynamic model which considers the effects of models on a timeframe. In this model, farmers make decisions on a yearly basis where their income is subjected to income in year T. In equation (2), the underlying factors that make changes to farmers' decisions is the mean of the income and the variance of the income. The climate change variable, C, is affecting the expected income in 2 ways. First, it affects the mean of the income of farmers and second, if variance of income increases, farmers can decide to buy insurance to reduce impact of increased variance from C.

When farmers face weather realization in one year, they update their distribution of climate with new information. In the context where climate change notion is introduced, the scale of this climate distribution update may be larger if (1) farmers believe in the changing climate (denoted as climate change) and a weather shock confirms their belief or (2) farmers face strong weather shocks that deviate from the distribution.

Thus, farmers would only buy more insurance if they perceive higher risk in the previous year, and they seek ways to mitigate risk in this year. Price risk would be absorbed in the time-fixed effects because this component will be absorbed out by the national commodity price risk. However, the risk at a county level would not be absorbed by time fixed effects. Deviations of weather realizations from the historical climate distribution in that county would entice farmers to purchase more insurance.

# CHAPTER 4 DATA DESCRIPTIONS

## 4.1 Data Sources and Data Processing

Data in this study consist of 3 major sets of data: (1) crop insurance and corn production data from Risk Management Agency (RMA) and National Agricultural Statistics Service (NASS) respectively, (2) weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), and (3) Yale Climate Opinion data from Yale Program on Climate Change Communication.

### 4.1.1 Crop Insurance and Crop Production Data

The USA federal crop insurance data is obtained from the Risk Management Agency, a subsidiary of the United States Department of Agriculture (USDA). In this paper, I used the RMA report generator to obtain the crop insurance data particularly for corn for all the US counties from 1989-2016. The obtained variables include premium, subsidy, number of policies sold, liabilities, insurance types, levels of coverage, indemnities, number of insured acreage, and loss ratio.

Production data is obtained from the National Agricultural Statistics Service (NASS). The dataset is specifically obtained for corn production data in each county in the USA from 1990-2015. It includes number of planted acreage, number of harvested acreage, and amount of production.

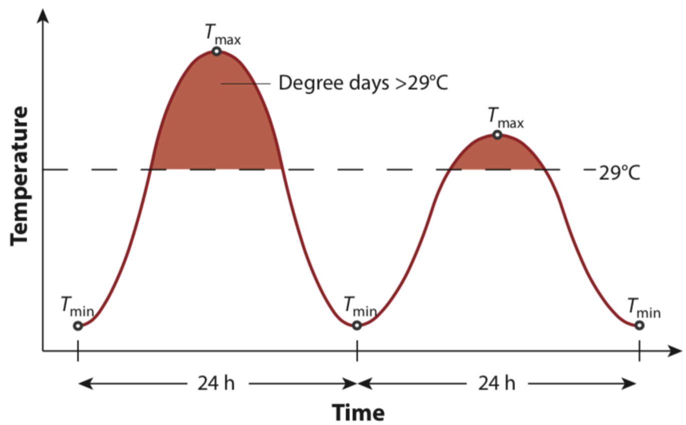
### 4.1.2 Weather Data

The weather dataset was obtained from the PRISM website. The database is curated and maintained by Oregon State University. It consists of temperature bin data of all counties in the US and spans from 1989 to 2016. The data is gridded with the resolution of 0.5x0.5 km and extrapolated from the weather ground stations.

I construct a new variable called growing-degree days. Illustrated in Figure 5.1, growing degree days is a common measurement used in agronomic literature to measure accumulative temperature throughout crop growing seasons. It is adopted in studies in economic impacts of climate change as well. It captures the amount of heat a region is exposed to a range of temperature in a range of time.

In my study, I aggregate the GDD from April to September, a common crop growing season across the US. I aggregate the data with spatial polygon data by county coordinates to obtain temperature bin data by counties. It captures the heat through which plants may use for biological growth or heat that may affect humans' perception.

*Figure 4-1: Degree-day measurement (Source: Hsiang 2016)*



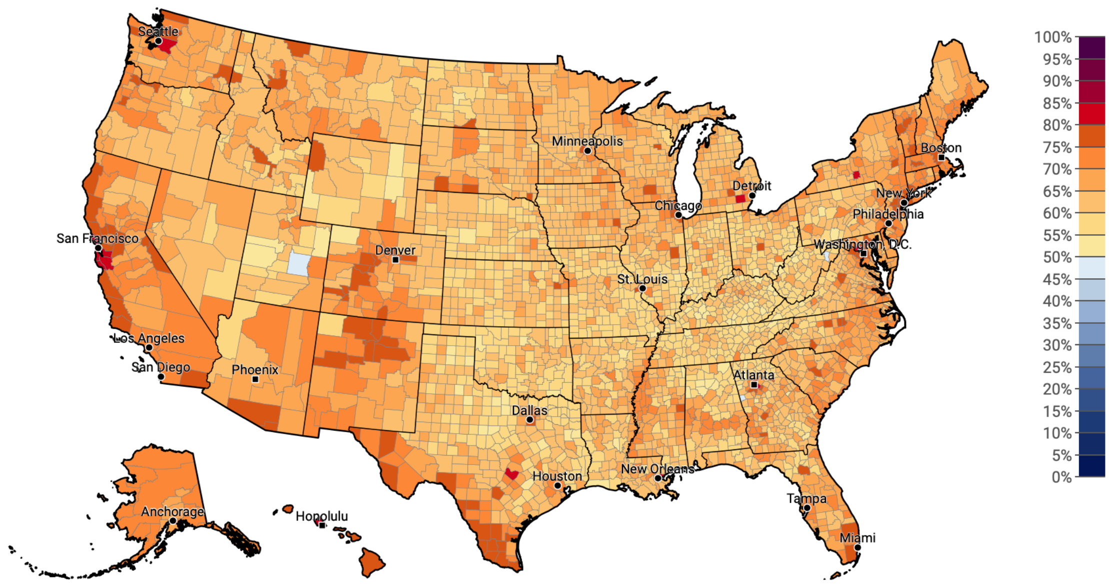

### 4.1.3 Climate Belief Data

The climate opinion data is obtained from the Yale Climate Opinion Group. The data is cross-sectional and spans across all counties in the US. The period of the data is only in the year 2014, the earliest year of climate opinion data I could find on the website.

*Table 4-1: Summary Statistics of Climate Opinion Data*

| Variables | n | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| Share of population who believe in climate change (%) | 1,104 | 58.47 | 3.84 | 47 | 76 |

*Figure 4-2: Share of Population that Believes in Global Warming in Year 2018 (Source: Yale Program on Climate Change Communication)*




## 4.2 Constructed Variables

For the crop insurance and corn production data, after cleaning data by removing observations with missing values, the data are joined by FIPS numbers and years. Then, I construct the following variables: yield (production/harvested acreage), indemnity per acreage (indemnity/harvested acreage), premium per acreage (premium/planted acreage), and subsidy per acreage (subsidy/planted acreage), and willingness to pay per acreage (premium per acreage – subsidy per acreage). The dataset is analyzed by regions, including the main corn-growing regions (Midwest and its subunit with soil qualities particularly suited for corn growth, Corn Belt), east and west of the 100$^{th}$ meridian line, and the entire country. I also log-transformed some variables, such as yield, for normality.

### 4.3 Descriptive Statistics

The above dataset can be summarized after the removal of missing data and outliers as below:

*Table 4-2: Summary Statistics of Corn Insurance and Production Data*

| Variables | n | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| Crop Year | 31,088 | 2,003 | 7 | 1,991 | 2,015 |
| Insured Land Ratio | 31,088 | 0.66 | 0.24 | 0 | 1.00 |
| Premium Per Acre ($/Acre) | 31,088 | 25.54 | 19.85 | 0.80 | 130.50 |
| Indemnity Per Acre ($/Acre) | 31,088 | 22.99 | 48.53 | -0.01 | 755.46 |
| Weighted Policies Sold (Policies/1,000 acres) | 31,088 | 112 | 248 | 1 | 14,000 |
| Number of Insurance Policies Sold | 31,088 | 314 | 322 | 4 | 3,726 |
| Indemnity ($) | 31,088 | 1,058,174 | 3,933,738 | (1,402) | 139,564,111 |
| Insured Acreage (Acres) | 31,088 | 40,887 | 48,652 | 4 | 360,277 |
| Yield (Bushels/Acre) | 31,088 | 125.44 | 36.52 | 4.55 | 239.13 |
| Planted Acreage (Acres) | 31,088 | 57,289 | 58,585 | 300 | 397,000 |
| Harvested Acreage (Acres) | 31,088 | 53,147 | 57,210 | 100 | 394,000 |
| Production (Bushels) | 31,088 | 7,629,524 | 9,312,342 | 1,000 | 77,224,000 |

*Table 4-3: Summary Statistics of Weather Data*

| Variables | n | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| Growing degree days from 10 - 30 degree Celsius (GDD10-30) | 31,088 | 36,803 | 5,137 | 18,974 | 53,069 |
| Growing degree days from 30 - 50 degree Celsius (GDD30-50) | 31,088 | 1,034 | 1,100 | 0 | 14,527 |
| Precipitation (millimeters) | 31,088 | 426 | 178 | 35 | 1,866 |
| Precipitation$^2$ (mm$^2$) | 31,088 | 213,022 | 187,316 | 1,229 | 3,483,309 |

# CHAPTER 5 ECONOMETRIC MODELS AND METHODS

To show that farmers are really changing their crop insurance demand after weather shocks, I will need to show that after experiencing unusual weather, farmers have changed their crop insurance demand in the following year(s). I use a reduced form approach and use the exogenous nature of the weather shocks to identify changes in crop insurance demand after years of weather shocks. The following is the distributed lag panel model, which I used to identify the effects of weather events.

$$y_{it} = \sum_{n=1}^{n=N} \alpha_{t-n} X_{it-n} + \sum_{n=1}^{n=N} \beta_{t-n} Z_{it-n} + \theta_i + \delta_t + \lambda_{it} + \epsilon_{it}$$

$y_{it}$ denotes corn insurance variables, such as insured land ratio, weighted number of policies sold, and premium per acreage in county *i* and in year *t*. $X_{it-n}$ denotes lagged effects of good weather variables, such as degree days from 10-30 degree Celsius, *n* years before year *t* with corresponding $\alpha_n$. $Z_{it-n}$ denotes lagged effects bad weather variables, such as degree days from 30-50 degree Celsius, *n* years before year *t*. $\theta_i$ is county fixed effects, which account for time-invariant characteristics, such as soil characteristics and farmers' demographic characteristics (educational level, wealth, and age). $\delta_t$ is year (time) fixed effects, which account for the time-varying effects, such as technological change, nationwide policy implementation, macroeconomic conditions (inflation and interest rate) and price effects of corn futures and inputs. $\lambda_{it}$ is controls for county *i* and year *t*, including the price of corn insurance and price and availability of corn insurance in that county in that year. $\epsilon_{it}$ is idiosyncratic shock in county *i* and year *t*.

The distributed lag panel model aggregates the effects of weather shocks in the previous years on year t.

## 5.1 Empirical Strategy

In this paper, I approach the empirical problem as the following. I identify the channels through which weather shocks can affect crop insurance demand. The two major channels in which I hypothesize that the weather shocks will affect crop insurance demand are wealth effects and then belief effects. We first identify how weather shocks, in this case, precipitation and accumulated heat, yields of crops. Then, I identify how farmers are reimbursed for their revenue loss through indemnity payments from these weather events. Then, I identify how these indemnity payments affect their crop insurance demand. Then, I regress crop insurance demand directly on levels of weather variables and compare results with the effects of indemnity payments. Lastly, I identify how opinions of climate beliefs can explain degrees of changes of crop insurance demand with cross-sectional data of the climate opinion.

After elimination of missing values and outliers, I explore the data with maps, and then, I chose the model for plotting. Then, I run regression tests in R. I aggregate temperature 10 years prior to the year of crop insurance data and estimate the effects of those aggregated temperature bins on the crop insurance take-up.

## 5.2 Nonlinearities of Weather Variables

The weather shocks in this paper are defined as the level of extreme degree days (growing degree days from 30 to 50 degree Celsius), a temperature range that is non-supportive for plant growth. The insurance demand is captured through different variables, namely, insured acreage, normalized insured land ratio, willingness to pay per acre, liability per acre, and the weighted number of policies sold. The extreme degree days will affect both mean and variance of the extreme degree days.

For the piecewise linear model, I use two ranges of temperature that spans the growing season from April to August. Insurance demand is calculated as the willingness to pay and share of insured land.

In the case of weather variables and crop yield, the model for crop growth is the following:

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)dh + z_{it}\delta + c_i + \epsilon_{it}$$

where the growth of plant $g(h)$ depends nonlinearly on heat h. $\phi_{it}(h)$ is the time distribution of heat over the growing season. Then, I used the following econometric model to estimate the above integral.

$$y_{it} = \sum_{10}^{50} g(h + 0.5)[\phi_{it}(h + 1) - \phi_{it}(h)] + z_{it}\delta + c_i + \epsilon_{it}$$

### 5.3 Panel Fixed Effects Model

Panel fixed effects model assumes that the effects of certain variables are fixed. The examples include time and area. For the model that I use in this study, I know that there is a time trend in crop insurance take-up as well as policies enacted throughout the studied period. Therefore, to correct for time-varying characteristics, I include year-fixed effects to account for those effects. Year fixed effects account for corn price, technological change, national policy effects, and macro-economic conditions, such as interest rates and inflation. Year fixed effects, in this case, can control for the small rise of mean and variability of climate over time and the gradual increase in insurance adoption. They also control for aggregate time series trend. This includes the rise of discussion in climate change, the rise of insurance subsidy, technology adoption, availability of insurance policy. With the US crop insurance market marked with several policy enactments, these policies also play crucial roles in insurance participation. With crop insurance demand purchase decisions being made once a year, including year fixed effects will obscure the effects of other yearly variables that affect crop insurance demand, such as corn price and discussion of weather shocks.

I also include county fixed effects as well to account for time-unvarying characteristics in each county, such as soil characteristics and farmers' demography. They are a common fixed effect to include in the panel study in economic impacts of climate change.

### 5.4 Clustered Robust Standard Error

Because weather variables can be correlated across space and time, the standard errors without clustering would be biased. Conley (1999) proposed an econometric model to estimate the response in cross-sectional dependence. The standard errors are clustered two-way with state-year. Using clustered-robust standard error, instead of assuming constant standard error, is suggested to correct for biased standard error (Cameron et al. 2015).

## 5.5 Bayesian belief updating model

In dynamic model, I have that farmers update their beliefs about their crop insurance with Bayesian belief updating. I use that farmers update their decisions on a yearly basis using observations of weather from previous year as the main realization. The process in which farmers update their beliefs about climate conditions is the following:

$$\mu_T = \frac{\tau_t \mu_t + T\rho\bar{z}}{\tau_t + T\rho}$$

where $\mu_T$ represents beliefs about climate condition in year T. Every year that farmers observe weather realization, they average their beliefs about climate conditions within the t-distribution framework. In this setting, I evaluate the effects of weather on crop insurance demand using different lag levels, namely 1, 3, 6, and 9. I assume farmers estimate their climate distribution in year T from estimating mean and variance of the previous observations under t-distribution.

When farmers experience climate conditions in year T, their realized profits are affected. They update their beliefs about their productivity in the following year. This is updated through $\frac{d\kappa(C)}{dC}$ and $\frac{dV(C)}{dC}$.

I can use the belief updating model developed by DeGroot (1970) and apply Burke and Emerick (2016)'s method to crop insurance market. In a market where farmers experience climate change, the mean temperature (or rainfall) shifts from $w$ to $w'$, and the variance $\sigma^2$ changes to $\sigma'^2$. Farmer experiences weather realization $z_{it} \sim N(\acute{w}_t, \acute{\sigma}^2)$ in each year. Given farmers' prior belief about climate in period t is $w_t$, which follows normal distribution with mean $\mu_t$ and variance $1/\tau_t$: $w_t \sim N(\mu_t, 1/\tau_t)$. Farmers update their beliefs about average temperature (rainfall) to $\mu_{t+1}$after they observe weather realization $z_{it}$ in period t. Then, let $\bar{z}$ denote average of temperature (rainfall) realizations during period T-1 years and $\rho = 1/\sigma^2$, and the farmers' belief about mean climate after T years is:

Combining equations (6) and (7), I will have that farmers will incorporate changes in mean and variance of temperature (rainfall) into their beliefs about climate. With changes that farmers expected, changes in year t will be able to expect the changes in year t+1.

## 5.6 Cross Validation Model

To have a benchmark of what models can best explain variations in the crop insurance demand, I use a k-fold cross-validation model, a machine learning method, to compare the performance of different models to predict the outcome. The method uses the training set and test set to approximate how much variations the model with explanatory variables can reduce.

# CHAPTER 6 RESULTS

In this chapter, I empirically investigate how weather shocks affect crop insurance demand during the period of 1991-2015 at county level in specific regions in the US and the entire country, using crop insurance data, crop production data, weather data, and climate belief data. I first examined if variations in one-year lagged effects of weather variables can explain changes in crop insurance demand variables in the Midwestern States. Then, I tested the lagged weather effects across regions and time to identify possible mechanisms that can explain crop insurance demand, employing methods and results from previous literature to enliven the results. After verifying that the lagged weather effects are statistically significant in certain regions in the US and timeframe, I examine channels that weather shocks can have effects on insurance demand. Farmers' wealth and beliefs are considered. For the wealth effects, I examine how weather shocks can possibly affect farmers' wealth, and for the belief effects, I use climate opinion data to examine how beliefs in climate can affect crop insurance decisions. The results point towards heterogeneity in farmers' response towards weather shocks across space and time.

## 6.1 Identification of Weather Effects on Crop Insurance Demand

In Table 6-1, I first consider the immediate effects of weather shocks on crop insurance demand. I show that the effects of one-year lagged weather variables are statistically significant on crop insurance demand. The one-year lagged extreme degree days (GDD30-50) has statistically significant effects on both insured land ratio and weighted policies sold. For the insured land ratio variable, the one-year lagged extreme growing degree days has positive effects on the insured land ratio, which means that a 1,000-unit increase in extreme growing degree days in the previous year during the growing season is associated with the increase of the participation rate of corn planted acreage in a crop insurance program of 2% on average in the following year. The adjusted R-squared is quite high for the models with fixed effects, but the adjusted R-squared for the projected model, which is the model after subtracting effects of fixed effects out, is negative.

*Table 6-1: Effects of Lagged Weather Variables on Corn Insurance Demand for the Midwestern States from 1991-2015*

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | *Insured Land Ratio* | *Premium Per Acre ($ per acre)* | *Weighted Policies Sold* | *Insured Acreage (Acres)* |
| | (1) (x $10^{-5}$) | (2) (x $10^{-4}$) | (3) (x $10^{-3}$) | (4) |
| GDD 10 - 30 °C, 1 lag (degree days) | 13.26 | 1.720** | -1.830 | 0.549 |
| | (26.15) | (0.768) | (2.264) | (0.424) |
| GDD 30 - 50°C, 1 lag (degree days) | 1.903*** | 5.072 | 20.66*** | -1.077 |
| | (0.665) | (7.140) | (6.780) | (1.186) |
| Precipitation, 1 lag (Inches) | 3.488 | -10.79 | 48.95* | -4.104 |
| | (2.345) | (23.02) | (28.58) | (4.729) |
| Precipitation$^2$, 1 lag (Inches$^2$) | -0.00343** | 0.01052 | -0.05663* | 0.0013 |
| | (0.00151) | (0.01861) | (0.03302) | (0.0043) |
| $R^2$ (Projected Model) | 0.0045 | 0.0019 | 0.002 | 0.0063 |
| $R^2$ (Full Model) | 0.83 | 0.92 | 0.37 | 0.92 |
| Adjusted $R^2$ (Projected Model) | -0.0483 | -0.0511 | -0.051 | -0.0464 |
| Adjusted $R^2$ (Full Model) | 0.823 | 0.911 | 0.332 | 0.919 |
| Residual Std. Error (df = 18,755) | 0.096 | 6.033 | 212.839 | 14974.83 |
| Observations | 19,752 | 19,752 | 19,752 | 19,752 |

*Notes: *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.*

*Table 6-2: Compound Effects of Lagged Weather Variables on Corn Insurance Demand for the Midwestern States (1991-2015)*

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *Insured Land Ratio* | *Premium Per Acre* | *Weighted Policies Sold* | *Insured Acreage* | *Insured Land Ratio* | *Premium Per Acre* | *Weighted Policies Sold* | *Insured Acreage* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| F- Score and p-value for Models with GDD 10 - 30 °C and GDD 30 - 50 °C Cumulative Effects, Each Variable with 5 lags for Projected Model | -1.417<br>(1) | 0.8709<br>(0.5825) | 2.006<br>(0.1346) | 13.98***<br>($7.095 \times 10^{-5}$) | | | | |
| F- Score and p-value for Models with GDD 10 - 30 °C and GDD 30 - 50 °C Cumulative Effects, Each Variable with 10 lags for Projected Model | | | | | -0.05196<br>(1) | 0.1065<br>(1) | -0.3139<br>(1) | 26.07***<br>($1.48 \times 10^{-6}$) |
| $R^2$ (Projected Model) | 0.0098 | 0.0048 | 0.006 | 0.0074 | 0.0098 | 0.0048 | 0.006 | 0.0074 |
| $R^2$ (Full Model) | 0.833 | 0.916 | 0.368 | 0.924 | 0.833 | 0.916 | 0.369 | 0.924 |
| Adjusted $R^2$ (Projected Model) | -0.0431 | -0.0484 | -0.0471 | -0.0457 | -0.0431 | -0.0484 | -0.0471 | -0.0457 |
| Adjusted $R^2$ (Full Model) | 0.824 | 0.911 | 0.335 | 0.92 | 0.824 | 0.912 | 0.335 | 0.92 |
| Residual Std. Error (df = 18,755) | 0.095 | 6.026 | 212.468 | 14,963.17 | 0.095 | 6.019 | 212.448 | 14,946.60 |
| Observations | 19,748 | 19,748 | 19,748 | 19,748 | 19,743 | 19,743 | 19,743 | 19,743 |

*Notes:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ Numbers in the parentheses are standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects.

In Table 6-2, I tested different lag specifications and cumulative effects of growing degree days on insurance variables, including 5-year and 10-year lags. With both models of 5 lags and 10 lags, insured acreage is significant. Also, note that for regression models for insured land ratio, 1-year, 2-year, and 3- year lag effects of growing degree days for 30-50 degree Celsius are statistically significant for both the 5-year-lag model and 10-year-lag models, but the F-statistics of both models do not indicate significant difference from the baseline model.

*Table 6-3: Effects of Lagged Weather Variables on Corn Insurance Demand for Different Regions in the US (1991-2015)*

| | *Dependent variable: Insured Land Ratio* | | | | |
|---|---|---|---|---|---|
| | (1) (x $10^{-6}$) | (2) (x $10^{-6}$) | (3) (x $10^{-6}$) | (4) (x $10^{-6}$) | (5) (x $10^{-6}$) |
| GDD 10 - 30 °C, 1 lag (degree days) | 2.409 | 1.256 | 1.319 | 0.4275 | 0.4816 |
| | (3.912) | (2.587) | (2.324) | (1.723) | (1.673) |
| GDD 30 - 50°C, 1 lag (degree days) | 11.97 | 19.00*** | 0.2277 | 15.92*** | 14.26*** |
| | (17.98) | (6.610) | (6.806) | (4.434) | (3.950) |
| States by Regions | Corn Belt | Midwest | West of 100th Meridian | East of 100th Meridian | USA |
| $R^2$ (Projected Model) | 0.0016 | 0.0042 | 0.0004 | 0.0049 | 0.004 |
| $R^2$ (Full Model) | 0.857 | 0.832 | 0.79 | 0.816 | 0.814 |
| Adjusted $R^2$ (Projected Model) | -0.0498 | -0.0486 | -0.1191 | -0.0571 | -0.0609 |
| Adjusted $R^2$ (Full Model) | 0.849 | 0.823 | 0.765 | 0.805 | 0.802 |
| Residual Std. Error | 0.088 (df = 9,451) | 0.096 (df = 18.757) | 0.122 (df = 1932) | 0.105 (df = 27224) | 0.107 (df = 29183) |
| Observations | 9,938 | 19,752 | 2,164 | 28,922 | 31,087 |

*Notes: *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.*

Table 6-3 shows changes of lagged weather shocks on insured land ratio. The one-year lagged extreme degree days has statistically significant positive effects on the insured land ratio in counties in states in Midwest, eastern side of the 100$^{th}$ meridian line, and the entire US. A 1,000 unit increases of GDD30-50 in counties in states in the Midwest and east of the 100$^{th}$ meridian line are expected to have increase in insured land ratio in the following year by 2 percentage points, and the increase of insured land ratio is expected to be 1 percentage point for the entire US.

*Table 6-4: Effects of Lagged Weather Variables on Corn Insurance Demand for the Midwestern States and States East of the 100th Meridian in Different Periods (1991-2015, 1991-2002, 2003-2015)*

| | *Dependent variable: Insured Land Ratio* | | | | | |
|---|---|---|---|---|---|---|
| | (1) (x $10^{-6}$) | (2) (x $10^{-6}$) | (3) (x $10^{-6}$) | (4) (x $10^{-6}$) | (5) (x $10^{-6}$) | (6) (x $10^{-6}$) |
| GDD 10 - 30 °C, 1 lag (degree days) | 1.256 | -0.1040 | -0.7542 | 0.4275 | -1.190 | -0.3093 |
| | (2.587) | (3.739) | (0.6131) | (1.723) | (2.883) | (0.6106) |
| GDD 30 - 50°C, 1 lag (degree days) | 19.00*** | 16.77* | 2.775 | 15.92*** | 13.20 | 6.064* |
| | (6.610) | (8.754) | (4.263) | (4.434) | ( 8.124) | (3.098) |
| Periods | 1991-2015 | 1991-2002 | 2003-2015 | 1991-2015 | 1991-2002 | 2003-2015 |
| States by Regions | Midwest | Midwest | Midwest | East of 100th Meridian | East of 100th Meridian | East of 100th Meridian |
| $R^2$ (Projected Model) | 0.0042 | 0.0029 | 0.0012 | 0.0049 | 0.0028 | 0.0031 |
| $R^2$ (Full Model) | 0.832 | 0.809 | 0.864 | 0.816 | 0.799 | 0.847 |
| Adjusted $R^2$ (Projected Model) | -0.0486 | -0.1092 | -0.1045 | -0.0571 | -0.1349 | -0.117 |
| Adjusted $R^2$ (Full Model) | 0.823 | 0.787 | 0.85 | 0.805 | 0.771 | 0.829 |
| Residual Std. Error | 0.096 (df = 18,757) | 0.112 (df = 8,611) | 0.056 (df = 9,197) | 0.105 (df = 27,2224) | 0.120 (df = 12,566) | 0.071 (df = 14,284) |
| Observations | 19752 | 9580 | 10171 | 28922 | 14302 | 16005 |

*Notes:* *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.

In Table 6-4, I examine the effects of one-year lag variables across time in 2 regions that have previously shown statistically significant effects of lagged weather shocks on the demand of corn insurance, Midwest and east of the 100th meridian line. Interestingly, the results for the Midwest point out that the one-year lagged effect of extreme degree days is only statistically significant for the entire sample (1991-2015) and not in different periods separately. The insured land ratio for all counties in states east of the 100th meridian line, however, shows significant results in the entire sample and in the second half (2003-2015) of the data and not the first half (1991-2002). This calls in to question why the results are only significant in the second half and not the first half of the data in counties in states in east of the 100th meridian line and why they are not significant in the Midwest when examined separately.

## 6.2 Identify Channels of Effects of Weather Variables on Crop Insurance Demand

As explained in the Theoretical Model chapter, the channels through which weather shocks affect crop insurance demand can be attributed into 2 major channels: wealth effects and belief effects.

For crop insurance demand, I hypothesized that weather variables affect crop insurance decisions through wealth and beliefs effects about climate change, which represents risk perception of production.

### 6.2.1 Effects of Weather Variables on Farmers' Wealth and Crop Insurance Demand

To understand the persistence of this effect is important. Farmers may buy crop insurance following the year of weather shocks and not the year after. This is known as recency bias (Fudenberg and Levine, 2014), and the change in year-to-year crop insurance demand does not cause changes in the long-run (changes in beliefs about climate). In contrast to the effects of American Dust Bowl, which has a long-run effect on farm productivity in the Great Plains (Hornbeck 2012), the effects of climate conditions in recent years on crop insurance demand are not persistent.

Table 6-5: *Effects of Weather Variables on Yield for the Midwestern States in Different Periods (1991-2015, 1991-2002, 2003-2015)*

| | *Dependent variable: Yield (Bushels)* | | | | |
|---|---|---|---|---|---|
| | (1) (x $10^{-3}$) | (2) (x $10^{-3}$) | (3) (x $10^{-3}$) | (4) (x $10^{-3}$) | (5) (x $10^{-3}$) |
| GDD 10 - 30 °C (degree days) | 1.447 | 2.786*** | 3.403*** | 2.687*** | 2.500*** |
| | (1.061) | (0.878) | (1.153) | (0.7093) | (0.704) |
| GDD 30 - 50 °C (degree days) | -26.63*** | -20.27*** | -2.848 | -14.53*** | -13.57*** |
| | (7.329) | (4.18) | (2.526) | (3.481) | (3.086) |
| States by Regions | Corn Belt | Midwest | West of 100th Meridian | East of 100th Meridian | USA |
| $R^2$ (Projected Model) | 0.152 | 0.2175 | 0.0745 | 0.2069 | 0.192 |
| $R^2$ (Full Model) | 0.76 | 0.783 | 0.784 | 0.771 | 0.764 |
| Adjusted $R^2$ (Projected Model) | 0.747 | 0.772 | 0.759 | 0.756 | 0.749 |
| Adjusted $R^2$ (Full Model) | 15.650 (df = 9,452) | 16.710 (df = 18,758) | 19.043 (df = 1,933) | 17.916 (df = 27,225) | 18.312 (df = 29,184) |
| Residual Std. Error | 9,939 | 19,753 | 2,165 | 28,923 | 31,088 |
| Observations | 9939 | 19753 | 2165 | 28923 | 31088 |

Notes: *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.

In Table 6-5, the results indicate that optimal growing degree days have statistically significant positive effects on yield in most regions. The extreme growing degree days also have statistically significant negative effects in most regions. The adjusted R-squared for the projected model is high for all regions, except the model for west of the 100$^{th}$ meridian line.

*Table 6-6: Effects of Lagged Yield on Insurance Demand for Different Regions*

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | InsuredLandRatio | | | |
| | (1) | (2) | (3) | (4) |
| lag(Yield, 1) | -0.0003 | -0.0004$^{*}$ | -0.0003$^{*}$ | -0.0003$^{*}$ |
| | (0.0003) | (0.0002) | (0.0002) | (0.0001) |
| States by Regions | Corn Belt | Midwest | East of 100th Meridian | USA |
| R2 (proj model) | 0.0054 | 0.006 | 0.0043 | 0.0037 |
| Adjusted R2 (proj model) | -0.0457 | -0.0466 | -0.0578 | -0.0613 |
| Observations | 9,938 | 19,752 | 28,922 | 31,087 |
| $R^2$ | 0.857 | 0.832 | 0.816 | 0.814 |
| Adjusted $R^2$ | 0.850 | 0.824 | 0.805 | 0.802 |
| Residual Std. Error | 0.088 (df = 9452) | 0.096 (df = 18758) | 0.105 (df = 27225) | 0.107 (df = 29184) |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |
| | The regression includes clustered robusted standard error by state and year with county and year fixed effects | | | |

Table 6-6 shows that the one-year lagged yield has statistically significant negative effects on the insured land ratio. This suggests that an average yield increase in that county of one bushel per acre will result in a decrease of insured land ratio.

### 6.2.2 Effects of Weather Variables on Beliefs and Crop Insurance Demand

Apart from the wealth (direct) effect, I also examine how weather shocks can affect beliefs about climate distributions and consequently beliefs about climate change.

*Table 6-7: Effects of Beliefs about Climate Change and Weather Shocks on Crop Insurance Demand for a Cross-Sectional Model of Year 2014*

| | *Dependent variable:* | | |
|---|---|---|---|
| | *First Difference Insured Land Ratio* | | |
| | (1) (x $10^{-3}$) | (2) (x $10^{-3}$) | (3) (x $10^{-3}$) |
| GDD 30 - 50 °C (degree days) | -0.0762 | -0.01828 | -1.199 |
| | (0.1345) | (0.13574) | (2.050) |
| Proportion of Population who Believes in Global Warming in a County | | 3.989** | 4.522** |
| | | (2.002) | (2.205) |
| GDD 30 - 50 °C x Proportion of Population who Believes in Global Warming in a County | | | 0.02024 |
| | | | (0.03505) |
| Constant | -96.62*** | -327.8*** | -358.0*** |
| | (8.926) | (116.4) | (127.6) |
| $R^2$ (Projected Model) | 0.0003 | 0.0039 | 0.0042 |
| $R^2$ (Full Model) | 0.0003 | 0.004 | 0.004 |
| Adjusted $R^2$ (Projected Model) | -0.0006 | 0.0021 | 0.0015 |
| Adjusted $R^2$ (Full Model) | -0.001 | 0.002 | 0.001 |
| Residual Std. Error | 0.250 (df = 1,102) | 0.250 (df = 1,101) | 0.250 (df = 1,100) |
| Observations | 1104 | 1104 | 1104 |

*Notes:* *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.

*Table 6-8: Effects of Beliefs about Climate Change and Weather Shocks on Crop Insurance Demand for a Panel Model from 1991 to 2015 with Climate Belief Data from Year 2014*

| | Dependent variable: | | |
|---|---|---|---|
| | *Insured Land Ratio* | *Premium Per Acre ($ per acre)* | *Weighted Policies Sold* |
| | (1) (x $10^{-5}$) | (2) (x $10^{-3}$) | (3) (x $10^{-3}$) |
| GDD 10 - 30 °C (degree days) | 1.969 | 1.033 | -1.633 |
| | (1.665) | (1.111) | (6.137) |
| GDD 30 - 50 °C (degree days) | 8.446 | -0.6113 | 23.20 |
| | (5.782) | (2.877) | 37.59 |
| GDD 10 - 30 °C x Proportion of Population who Believes in Global Warming in a County | -0.03228 | -0.01241 | -0.007961 |
| | (0.02753) | (0.01848) | (0.1050 |
| GDD 30 - 50 °C x Proportion of Population who Believes in Global Warming in a County | -0.1188 | 0.02322 | -0.2805 |
| | (0.09835) | (0.04733) | 0.6865 |
| $R^2$ (Projected Model) | 0.0282 | 0.0076 | 0.025 |
| $R^2$ (Full Model) | 0.028 | 0.008 | 0.025 |
| Adjusted $R^2$ (Projected Model) | 0.0281 | 0.0075 | 0.0249 |
| Adjusted $R^2$ (Full Model) | 0.028 | 0.007 | 0.025 |
| Residual Std. Error (df = 31082) | 0.237 | 19.776 | 244.806 |
| Observations | 31088 | 31088 | 31088 |

Notes: *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.

In Table 6.8, I use climate change belief data to estimate its effects of changes on the insured-land ratio in a cross-sectional setting for the year 2014 (the earliest data on climate change beliefs I could find). The variable "happening" denotes percentages of people who believe in climate change in that county. I show that in cross-sectional data of the year 2014, even though the change of extreme degree days in year 2013 does not explain changes in insured land ratio in year 2014. The effects of levels of share of population who believes climate change is happening are statistically significant and positive.

## 6.3 Robustness Checks

### 6.3.1 Other Explanations

*Table 6-9: Effects of Insurance Experience on Insured Land Ratio for the Midwestern States (1991-2015)*

| | *Dependent variable:* | | |
|---|---|---|---|
| | *Insured Land Ratio* | | *Indemnity Per Acre ($ per acre)* |
| | (1) (x $10^{-4}$) | (2) (x $10^{-4}$) | (3) |
| Yield, 1 lag (Bushels/Acre) | -3.504* <br> (2.043) | | |
| Indemnity per Acre, 1 lag ($ per acre) | | 1.798*** <br> (0.6959) | |
| Yield (Bushels/Acre) | | | -1.293*** <br> (-0.391) |
| $R^2$ (Projected Model) | 0.006 | 0.0063 | 0.3666 |
| $R^2$ (Full Model) | 0.832 | 0.832 | 0.636 |
| Adjusted $R^2$ (Projected Model) | -0.0466 | -0.0463 | 0.3331 |
| Adjusted $R^2$ | 0.824 | 0.824 | 0.617 |
| Residual Std. Error | 0.096 (df = 18,758) | 0.095 (df = 18,758) | 32.095 (df = 18,759) |
| Observations | 19752 | 19752 | 19753 |

*Notes:* *p<0.1; **p<0.05; ***p<0.01 Numbers in the parentheses are clustered standard errors. The regression includes clustered robusted standard error by state and year with county and year fixed effects. Degree days are accumulated from April to September of each year.

In Table 6-9, I test the insurance experience on farmers' insurance demand. The one-year lagged effect of indemnity per acre is statistically significant and positive. This indicates that 100-dollar increase in the indemnity payment per acre will result in the increase in insured land ratio by 0.02 units on average. The indemnity payment will result in increase in insured land ratio as well.

# CHAPTER 7 DISCUSSION

In the Results chapter, I examine effects of weather shocks on corn insurance demand, using corn insurance, corn production, weather, and climate opinion data. The results point to changes in underlying assumptions across regions and time.

I have shown that the effects of lagged weather variables are statistically significant on the crop insurance demand variables. The increase in extreme degree days in the previous year results in the increase of crop insurance uptake in the following year. This result applies to many regions in the US, including the Midwest and area east of the 100$^{th}$ meridian line. As expected, the effects are not observed in the area west of the 100$^{th}$ meridian line because much of corn farmland in the region is irrigated. Corn farmland is protected from the heat damage, and possibly dryness, by irrigation. Thus, response to weather shocks in crop insurance demand in the region is not observed.

The effects of weather shocks are also observed in the second half of the study (2003-2015) and not in the first half (1991-2002) in the states east of the 100$^{th}$ meridian line. It means that in the first half of the study, after a shock in extreme degree days, farmers do not respond to this shock by enrolling more land into the insurance programs. However, in the second half of the study, the response is evident, and farmers enroll more of their land in the crop insurance programs following a year of (heat or temperature) shocks from extreme growing degree days. I hypothesize that the changes in response behaviors in the second half come from changes in beliefs about climate change.

After verifying the lagged effects of weather shocks on crop insurance demand, I then proceed to identify the channels of lagged weather effects on insurance demand to identify the mechanisms through which weather shocks affect crop insurance demand. First, I examine the wealth effects. I identified how weather variables explain changes in yield and thus farmers' wealth. Optimal growing degree days has statistically significant positive effects on yield for most of the regions in the US. Extreme growing degree days has statistically significant negative effects on yield for most of the regions in the US, except counties in states west of the 100$^{th}$ meridian due to the more proportion of land with irrigation infrastructure in the region. However, the adjusted R-squared for the projected models, the adjusted R-squared after accounting for county and year fixed effects, are not high, in the range of 0.10-0.18. Then, I verify the lagged effect of yield, which is translated to farmers' annual farm income, on insured land ratio. I find that the lagged yield effect on insurance is again statistically significant for the insured land ratio but only at alpha level of 0.10.

To check for the belief effects, I use cross-sectional data of the share of population in each county who believe in global warming to explain changes in crop insurance demand and find that counties that have higher share of population who believe in global warming tend to have a larger reaction of insured land ratio to other counties that experience similar level of weather shocks in previous year. This confirms our theory that given the underlying belief of climate change in the second half of the study has changed due to much more discussion about climate change, but farmers are unsure whether the event is really happening (ambiguous information) and are reactive to changes, as the results indicate that farmers in eastern side of the 100$^{th}$ meridian line responds to heat shocks with crop insurance in the second half of the study.

# CHAPTER 8 CONCLUSION

In this paper, I have employed a panel dataset of climate variables, crop insurance, and corn production data to estimate changes in the crop insurance demand that are caused by weather shocks. I uniquely employ climate opinion data to identify underlying assumption about climate distributions in the economy and how that has affected decisions on purchasing crop insurance.

## 8.1 Contribution

This paper contributes to several lines of literature, including those in crop insurance demand and those in adaptation to climate change in the US agricultural sector. To the best of my knowledge, this is the first study to investigate the effects of beliefs of climate change on crop insurance demand. I have contributed understanding of the assumption that the US farmers are adapting to climate change with changes in beliefs about climate distributions and the mechanisms of how farmers change their insurance demand with regards to weather shocks with uncertain information about climate.

This study not only contributes to the fields of applied economics, but also contributes to the economic fields on decision making under risk. With this model, I can identify changes in responses of weather shocks across time and region.

## 8.2 Future work

The following is the list of possible works that could be done to shine more light in the study of climate change on farmers' crop insurance demand. They include work that can contribute to different areas of research in the specific fields of economic impacts of climate change and crop insurance and to economic theory.

Longer timespan of climate opinion data is needed to identify causal effects of beliefs of global warming on insurance demand. This study only uses cross-sectional data of climate opinion, and as such, it does not identify effects of opinions over time.

As mentioned in the economic model. Crop insurance demand can change due to changes in risk preferences as well. With the ongoing discussion of climate change in this period, it is possible that farmers' attitudes towards risk change.

With more data on household or individual levels, this study can extend to study economic behaviors of households or individuals after shock events, especially the effects of wealth on shock response and income smoothing.

Including the effects of news of climate change, such as the number of times it is covered in the news, would give more information on the effects of news and beliefs on the crop insurance demand. Including a panel data of beliefs in climate change over time would be crucial in understanding how people update beliefs about climate over time and will be an important framework to analyze farmers' decisions under the changing climate. Studying the neighborhood effects would also give a brighter perspective on how farmers learn from those around them.

# REFERENCES


Anderson, J. R., Dillon, J. L., & Hardaker, J. (1977). *Agricultural decision analysis*.

Annan, F., & Schlenker, W. (2015). Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *American Economic Review*, *105*(5), 262–266. https://doi.org/10.1257/aer.p20151031

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, *46*, 555–561. https://doi.org/10.1016/j.eneco.2014.09.010

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, *124*(1), 105–159. https://doi.org/10.1086/684582

Burke, M., & Emerick, K. (2016). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–140. https://doi.org/10.1257/pol.20130025

Cameron, Colin, A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

Chen, Z., & Dall'Erba, S. (n.d.). *Do crop insurance programs preclude their recipients from adapting to new climate conditions?* 34.

Coble, K. H., Knight, T. O., Miller, M. F., Goodwin, B. J., Rejesus, R. M., & Boyles, R. (2013). Estimating structural change in US crop insurance experience. *Agricultural Finance Review*, *73*(1), 74–87. https://doi.org/10.1108/00021461311321320

Coble, K. H., Knight, T. O., Pope, R. D., & Williams, J. R. (1996). Modeling Farm-Level Crop Insurance Demand with Panel Data. *American Journal of Agricultural Economics*, *78*(2), 439. https://doi.org/10.2307/1243715

DeGroot, M. *H., 1970, Optimal Statistical Decisions*. New York: McGraw-Hill.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature †. *Journal of Economic Literature*, *52*(3), 740–798. https://doi.org/10.1257/jel.52.3.740

Deschênes, O., & Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *The American Economic Review*, *97*(1), 354–385.

Felkner, J., Tazhibayeva, K., & Townsend, R. (2009). Impact of Climate Change on Rice Production in Thailand. *American Economic Review*, *99*(2), 205–210. https://doi.org/10.1257/aer.99.2.205

Hanna, R., Mullainathan, S., & Schwartzstein, J. (2014). Learning Through Noticing: Theory and Evidence from a Field Experiment . *The Quarterly Journal of Economics*, *129*(3), 1311–1353. https://doi.org/10.1093/qje/qju015

Hansen, L. P. (2017). Uncertainty in Economic Analysis and the Economic Analysis of Uncertainty. *KNOW: A Journal on the Formation of Knowledge*, *1*(1), 171–197. https://doi.org/10.1086/692519

Hornbeck, R. (2012). The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe. *American Economic Review*, *102*(4), 1477–1507. https://doi.org/10.1257/aer.102.4.1477

Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, *8*(1), 43–75. https://doi.org/10.1146/annurev-resource-100815-095343

Kaiser, H. M., Riha, S. J., Wilks, D. S., Rossiter, D. G., & Sampath, R. (1993). A Farm-Level Analysis of Economic and Agronomic Impacts of Gradual Climate Warming. *American Journal of Agricultural Economics*, *75*(2), 387. https://doi.org/10.2307/1242923

Kelly, D. L., Kolstad, C. D., & Mitchell, G. T. (2005). Adjustment costs from environmental change. *Journal of Environmental Economics and Management*, *50*(3), 468–495. https://doi.org/10.1016/j.jeem.2005.02.003

Lambert, D. K. (1990). Risk considerations in the reduction of nitrogen fertilizer use in agricultural production. *Western Journal of Agricultural Economics*, 234–244.

Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The Impact of Global Warming on Agriculture: A Ricardian Analysis. *The American Economic Review*, *84*(4), 753–771.

Niewuwoudt, W. L., & Bullock, J. B. (1985). *The Demand for Crop Insurance*. 13.

O'Donoghue, E. J., & Tulman, S. A. (2016). The Demand for Crop Insurance: Elasticity and the Effect of Yield Shocks. *Working Paper*, 27.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598. https://doi.org/10.1073/pnas.0906865106

Schlenker, Wolfram, Hanemann, W. M., & Fisher, A. C. (2006). The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *The Review of Economics and Statistics*, 13.

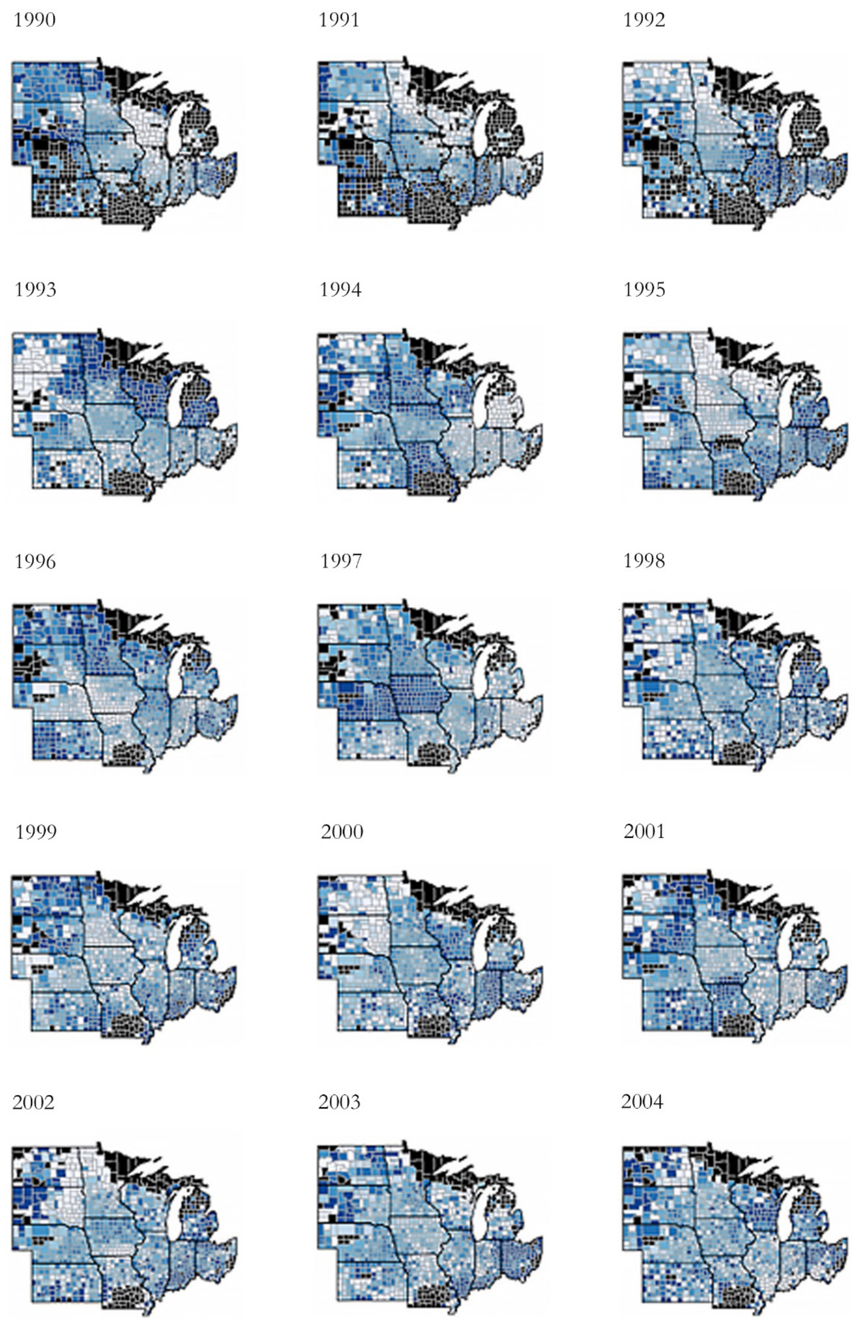
Schlenker, Wolfram, Michael Hanemann, W., & Fisher, A. C. (2005). Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review*, *95*(1), 395–406. https://doi.org/10.1257/0002828053828455

Shields, D. A. (2015). Federal Crop Insurance: Background. 27.

Wąs, A., & Kobus, P. (2018). Factors differentiating the level of crop insurance at Polish farms. *Agricultural Finance Review*, *78*(2), 209–222. https://doi.org/10.1108/AFR-06-2017-0054

# APPENDIX

*Figure A-1: Percentage of Changes in Insured Land Ratio in Midwest States*



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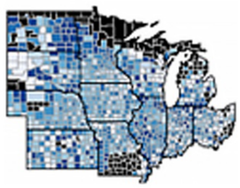

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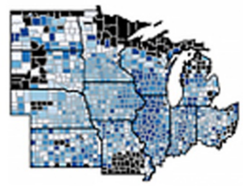

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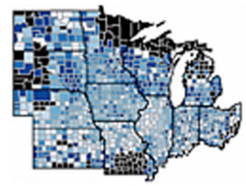

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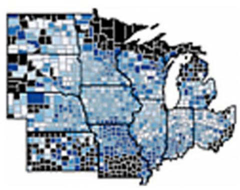

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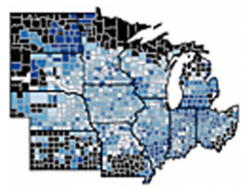

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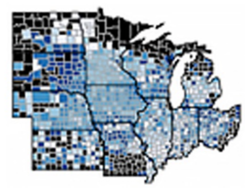

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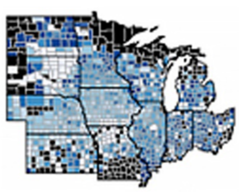

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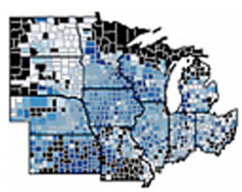

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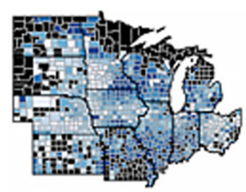

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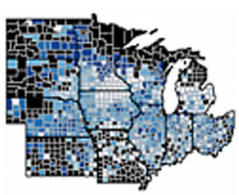
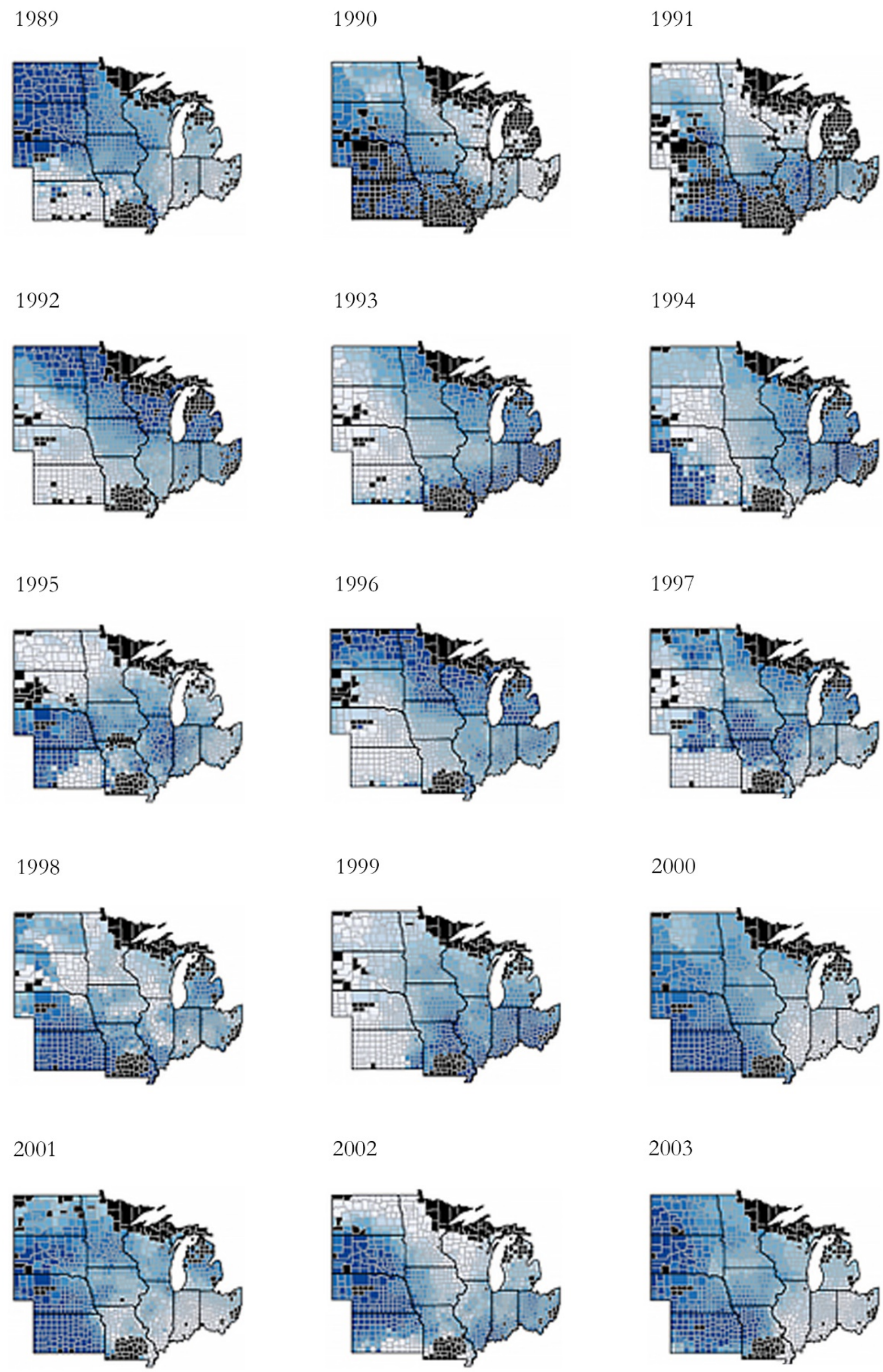
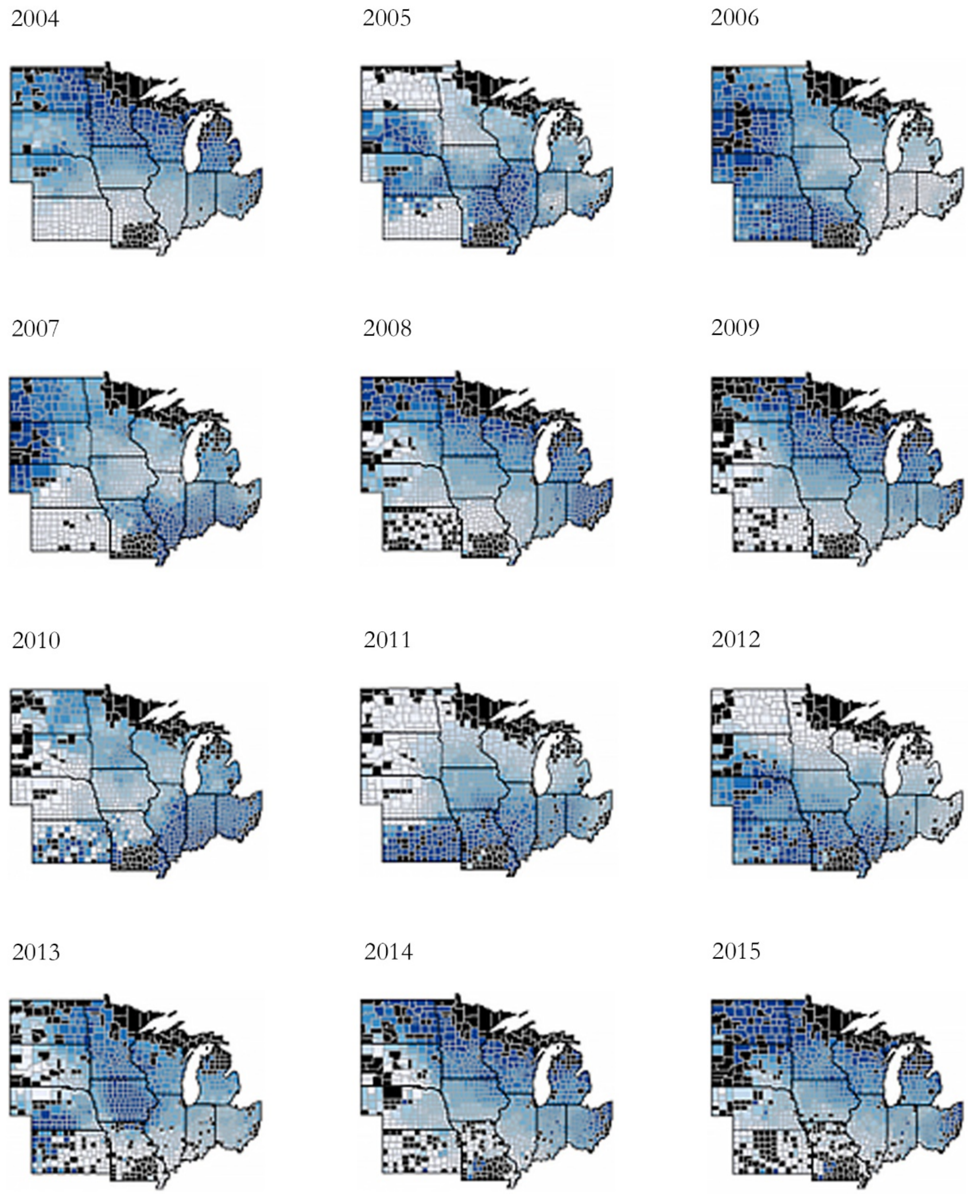


*Figure A-2: Percentage of changes in the insured-land ratio in each county in Midwest states from 1990-2014*

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