INVESTIGATING WEATHER SHOCKS AND THE FARMERS' PERCEPTIONS OF CLIMATE CHANGE IN THE AMERICAN FARMLAND MARKET

A Thesis

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ABSTRACT

U.S. agriculture is likely to be affected by climate change due to its inherent reliance on climatic inputs. An important difference among methods of climate change impact assessment is the treatment of farmer adaptation. While the cross-sectional Ricardian approach assumes that farmers have fully adapted to their current climate, panel methods assessing weather effects on profits assume farmers cannot fully adapt to idiosyncratic weather changes. Less is known, however, about the process of climate change adaptation and how farmers transition from practices adapted to a given climate to the next.

This thesis posits that farmers must first perceive that climate is changing as a prerequisite of engaging into adaptive responses. I test whether this first step in the adaptation process is occurring by exploiting the effect of random weather fluctuations on farm real estate, which reflects farmer perceptions about farm profitability. I develop a theoretical model to clarify the channels through which random weather shocks could affect farmland values, in which I consider farmers as Bayesian learners who update their priors about their mean climate based on experienced weather. I then rely on a distributed lag model to test the hypothesis.

I find no evidence that weather shocks have affected the farmland market. These findings are robust to geographic and temporal subdivisions. The results suggest that farmers do not perceive recent extreme weather as indications of sizable upcoming

changes in farm profitability. This may reflect the countervailing effect of agricultural prices and of government policies such as disaster payments.

BIOGRAPHICAL SKETCH

Matthew L. Utterback (Matthew Levy Utterback) was born in New York City, New York on September 7, 1985. He graduated from the University of Massachusetts, Amherst in May 2010 with a Bachelors of Science in Natural Resource Studies and minors in Resource Economics and Cultural Anthropology. After graduation, he worked domestically and internationally on environmental and natural resource management issues. This included a study on open space preservation with the Arava Institute of Environmental Studies, in Israel and briefly served with the United States Peace Corps, in Nicaragua. He is a Master of Science candidate in Applied Economics and Management at Cornell University.

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I of course owe incalculable gratitude toward my thesis committee, Drs. Ariel Ortiz Bobea and Jennifer Ifft. For all of the emails, meetings, clarifications, patience, and enduring support you have shown me during my time at Cornell, I am forever grateful. This thesis embodies a topic of research about which I have become impassioned, and I look forward to further dialogue and collaboration with both of you in the years to come. I would like to thank postdoctoral associates Dr. Haoying Wang and Dr. Leslie Verteramo. You both have been a pleasure to work with, and I cannot thank you enough for the insight you provided me while working on my thesis. Furthermore, I would like to thank Dr. Erika Mudrak of the Cornell Statistical Consulting Unit. I learned a tremendous deal from you and enjoyed our time working together.

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fuel me to keep on going on numerous occasions. I will carry it with me.

For ELU, JPU, and Izzy.

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CHAPTER 1
INTRODUCTION

Background

Over the last 55 years, the United States has experienced significant climate-related change.[1] Nationally, average temperatures have risen more than 2°F, and are projected to rise another 4°F - 11°F by the end of the 21st century (See Auffhammer et al.,2013; Burke et al.,2011 for an overview of the mechanics of GCMs and the respective models popularly used in climate change impact analysis). Changes in precipitation have been comparatively more variable, but overall precipitation and heavy precipitation events have increased in most regions.[2] The atmospheric variables air temperature, precipitation, and solar radiation, and their corresponding extremes of drought, heat stress, heavy precipitation and flooding, have been scientifically shown to be the most impactful factors in determining crop yields and livestock vitality (Adams et al.,1998). Considering this linkage, agriculture is said to have an inherent dependency on climate (Fox et al.,2011).

The United States of America's agricultural sector produced $330 billion United States Dollars (USD) of the nation's Gross Domestic Product (hereafter GDP) in 2014 (Hatfield et al., 2014). On a global scale, this monetary amount translates to being the world's largest producer and exporter of agricultural goods. Consequently,

[1] Succinctly climate change can be defined as the long-term shift in the statistics of weather - such as changes in average temperature and precipitation - at a specific location and over a certain period of time, ranging from decades to centuries.

[2] At the same time, the occurrence of drought has also been on the rise, particularly since 1970 (Allison et al., 2009).

food security and food prices around the world can be significantly influenced by the impact of weather on agricultural goods in the United States.

The agriculture sector's vulnerability to climate change is strongly dependent not only on these biophysical impacts, but on on how people adapt to said changes. In the context of this thesis, adaptation represents the change in an economic agent's behavior, in response to or in expectation of some event, so as to minimize damages or maximize benefits. Adaptation thus requires an agent to 1) recognize that something in his or her environment has changed, 2) believe that there is a more preferable course of action to their current state of being, and 3) have the capability of implementing that alternative course (Burke and Emerick, 2016).

Farmers in the United States have employed a number of strategies to adapt to climate change. These include changes in the the planting time, location, and rotation of crops; the usage of pesticides and fertilizers, substituting human labor with mechanized devices; water management; and the genetic development of crop types that are less susceptible to drought and flooding. While these have proven to be effective strategies to allow previous agricultural production to increase, as evidenced by the continued growth in production and efficiency across the United States, the accelerating pace of climate change and intensity of projected climate present new and unprecedented challenges (Hatfield et al., 2014; Kandlikar and Risbey, 2000).

Another risk management tool which farmers utilize to cope with a change in climate, stems from government programs and policies. Indeed, it is widely held that farm decisions do not occur in isolation, but may be influenced by government policies and programs (Cabrera et al., 2007). While farm programs can increase expected returns and/or reduce risks associated with a subset of the farmer's production decisions, they can also disincentivize farmers to react to a change in weather on their own. Consider for instance that future warming projections for most of the US might incentivize farmers to invest in more water efficient technologies or plant crops that are more heat resistant and drought tolerant (Lewandrowski and Brazee, 1993). With a case history of the federal government providing disaster assistance when crops fail or provide subsidies on irrigation infrastructure, there might be less prerogative for the farmer to spend their own capital to make such adjustments (Annan and Schlenker, 2015; Marzen and Ballard, 2016).[3]

Motivation

Agriculture is arguably one of the most researched sectors in the climate change impacts literature (Ortiz-Bobea, 2013). Over the last three decades, statistical and econometric approaches have become increasingly popular among economists in contrast to earlier biophysical process counterparts.[4] Significant disagreement persists in terms of the sign and magnitude of such impact on the agricultural sector (Fisher, Schlenker, Haneman, and Roberts, 2012).

[3]The conditions to receive disaster aid relief, qualify for crop insurance, or receive other subsidies via farm programs are summarized in http://www.rma.usda.gov., and USDA,2014.

[4]Much of the economic literature suggests that in the short term, producers will continue to adapt to weather changes and shocks. In the longer term, however, these adaptive strategies will likely no longer buffer producers and/or consumers from significant welfare loss (Hatfield et al.,2014).

This disagreement derives from the various ways in which economists model farmer adaptation to climate change, resulting in serious disparities. The climate change impact literature has progressed from explicitly limiting farmer adaptation (via the production function and crop simulation method) to implicitly assuming the farmer has adapted to their current climate (via the Ricardian method) and recently modeling farmer adaptation in response to weather shocks or assuming that the farmer is forward-looking. Despite these advances and improved usages of observational data to estimate the hypothetical impact of a change in climate on agricultural production or society's welfare, there is still a gap in the literature: the modeling of whether or not a farmer perceives (believes) that the climate has changed. The existence of this gap provides me with motivation to construct an additional test of farmers' perceptions of their local climate, and whether those perceptions have been changing.

Research Question

The main objective of this study is to examine if recent weather shocks are being capitalized by farmers in the United States through changes in farmland value. To accomplish this, I develop a distributed lag model, which allows me to investigate if a farmer's perceptions of weather is based on not only present day experience, but on recent past experiences as well. I part from previous methods that have modeled farmers as forward-looking, by constructing a panel of survey and fine-scale weather data, where causality is based on weather shocks. Although the usage of survey data to model farmers' perceptions of climate change is not new, by restricting my sample to only include the agricultural census and not an aggregate of surveys, I mitigate the issue of extrapolating farmers' perceptions from that of public opinion.[5] Moreover, I argue that by choosing to measure changes in farmland value over changes in crop yields, I will more easily be able to detect if changes in our dependent variable are reflective of a change in the farmer's perceptions, and not worry about disentangling the biological response from the behavioral one, which would be imperative, were I to use crop yields.

Contributions

Testing if weather shocks have been capitalized into the farmland market, provides the analyst with an additional metric to understand if the farmer has realized that the climate has changed and adapted to their new climate. How long it takes the farmer to believe that the climate has changed and consequently adapt to their new climate, is of pivotal importance on multiple levels. Kelly, Kolstad, and Mitchell (2005) emphasize that if a farmer is slow to realize that a change in weather is not just out-of-the ordinary weather, the transition costs a farmer may suffer due to suboptimal production decisions can be significant.

These adjustment costs not only affect the farmer's livelihood, but also how how agricultural government programs and payments will be drafted and implemented to off-set and minimize these potential losses. While this thesis is not a damage study and I do not calculate climate change impacts, it nevertheless contributes to the

[5] A concern with using aggregated indices of beliefs in climate change is that these are not as reflective of farmers as they are of the general public.

literature on adjustment costs where the farmer is assumed to be a Bayesian learner. Thus from a policy perspective, this thesis provides a template to measure the price signal that weather shocks have on farmland real-estate, and provides clarification on whether or not a market failure has occurred, in which case government intervention is justified.

Organization of Thesis

This thesis is organized as follows. Chapter 2 consists of a literature review of current approaches and issues in the climate change impact literature, as it relates to our research question. In Chapter 3, I discuss the theoretical model developed to examine how weather shocks are capitalized into the farmland market. In Chapter 4 I provide an overview of the empirical methodology that this study uses. The data sources and summary statistics for this study are discussed in Chapter 5. The empirical analysis is found in Chapter 6, along with a series of robustness checks. Concluding remarks, avenues for future research, and caveats to our findings are found in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

Methods to model the perceptions regarding climate change have included stated preference and revealed preference approaches. Those that have utilized the former have oriented their analysis around stated preference survey results. While there are a few institutions in the United States that survey public opinion on climate change, there are no recurrent surveys that include the agricultural sector's perceptions of climate change in the United States. These include the annual Gallup Environmental Survey, the Yale Project on Climate Change Communication, and the National Survey of American Public Opinion On Climate Change. And of those surveys that do target this stakeholder group, the scope is limited, and results (can be) difficult to interpret. For instance, Arbuckle et al.(2013) find that although Iowa is one of the states where temperature has changed the least in recent years, 65 % of the study's farmers in a recent survey indicated that they believe that "climate change is occurring" but only 35 % of them were concerned about the impacts of climate change on their farm operation.

An alternative approach to answer the question of whether farmers think the climate is changing is to rely on farmer-revealed preferences, which are implicitly embedded in observational data. With farm real estate representing much of the value of the U.S. farm sector assets, economists have sought to understand how weather and climate impact the farmland market by conducting land value studies, where the value of land is equal to the present discounted value of the future stream of profits that could be generated with a given parcel of land (Nickerson et al.,2012).[6] The theoretical foundation for nearly all of these studies is based on either the net present value (NPV) method or the hedonic pricing method. Below, a brief overview of the empirical strategies is reviewed.

Some of the earliest and most comprehensive studies to estimate the impacts of climate change on agriculture were via the production function approach (see Adams,1989; Kaiser et al.,1993). This approach examined the effect of weather on specific crop yields. However, a significant disadvantage of the production function approach is its inability to account for the full range of adaptive strategies that the farmer could make in response to weather changes (Dell et al.,2014). For instance: in response to a change in climate, a farmer could sell off farmland or adopt a new storage strategy. By not allowing a full range of adjustments, these studies tend to generate estimates which overestimate damages.

To address these concerns, Mendelsohn, Nordhaus and Shaw (hereafter MNS,1994) developed an approach which they called the Ricardian method, named after David Ricardo, who deduced that the value of land reflects its net productivity. MNS 1994 consisted of a cross-sectional regression of land values on historical climate variables. To account for global warming, average temperature and average precipitation were increased by 5°F and 8 %, respectively.[7] The authors conclude that during the second half the of the 21st century, land values will either decrease by 4-6 % or increase

[6] In principle, this land value embodies any possible long-term adaptation to climate change.

[7] These projections were first used in the 1990 IPCC Scientific Assessment on Climate Change, and correspond to the benchmark doubling of pre-industrial GHG levels.

by 1 %, depending on whether the model was weighted by cropland acres or crop-revenues. However, unlike the production function's approach to adaptation, the Ricardian approach takes the opposite extreme and has an implicit assumption that a farmer has full selectivity of adaptation strategies to employ. when in reality, farmers rarely have multiple adaptation strategies which are feasible and appropriate. Implicitly allowing for a full spread of adaptation measures,however, has consequences. The chief concern is that it is likely that these estimates suffer from omitted variable bias due to collinearity between climate variables and time-invariant unobservables (Schlenker,Hanemann, and Fisher, 2006 ; Deschênes and Greenstone, 2007; Fisher,Hanemann,Schlenker, and Roberts, 2012).

The comparison of climate change impact estimates through the inclusion and omission of control variables is one method to mitigate and detect time-invariant omitted variable bias.[8] Two prominent control variables found in climate change impact literature are irrigation and potential land development. Each has been empirically shown to significantly influence farmland. Plantinga et al.(2002) find that farmland close to urban areas inflates land values, because of the option value of land for urban development. Concluding that the highly subsidized price of irrigated water and its uncertain future availability biases pooled estimates, Schlenker,Hanemann, and Fisher (2005) emphasize the importance of accounting for irrigation in the Ricardian model.[9] The usage of control variables does not inform us of the strength of

[8]The logic behind such an approach is based upon the idea that if control variables are weakly correlated with climate variables, then the climate change estimates across models should be stable (Ortiz-Bobea, 2016).

[9]In their study, Schlenker,Hanemann, and Fisher (2005) define an irrigated county is one where at least 20 percent of said county's harvested cropland is irrigated. Those counties with less than 20 percent of irrigated farmland are referred to as dry counties.

the collinearity between climate variables and unobservables, and as such it is not a definitive solution to time-invariant omitted variable bias (Ortiz-Bobea, 2016).

More recent studies have shifted from a cross-sectional to a panel method approach to address this time-invariant omitted variable bias, and the relationship between agricultural output and weather variation. Instead of long-run climate averages being the explanatory variables of interest, year-to-year changes in temperature, precipitation, and other climatic variables tend to become the focus. The usage of weather shocks to isolate impact of climate variables on agriculture is a specific type of panel method approach that has strong identification properties. Using exogenous variation in weather outcomes over time (and within a given spatial location), this approach has the power to causatively identify the effects of weather variation on agricultural output. A risk of using this approach is the inclusion of time-varying observables. Although the inclusion of these can absorb residual variation, the empiricist can still run into the omitted variable bias problem, and the over-controlling problem that also complicates the cross-sectional approach (Dell et al.,2014; Hsiang,2016).[10]

The continued debate on how climate change will impact agriculture can in part be attributed to how these revealed-preference studies have reflected adaptation in their theoretical and empirical application. As briefly mentioned in the Introduction, broadly speaking, adaptation in climate change literature signifies the changing of one's behavior in response to or in expectation of some climatic phenomena, so that

[10]Hsiang (2016) notes that time-varying omitted variable bias arises if there are (important) time-varying factors that influence both the outcome and are correlated with climate variables, after being conditioned.

damages from said phenomena are minimized or the positive benefits are maximized (Tol et al.,1998).

An assumption in the Ricardian literature is that farmers have adapted to their local climatic conditions. This implies that they are exhibiting profit-maximizing behavior. However, behavioral decision research over the last 40 years provides a series of lessons about the importance of affect in perception of risk and in decisions to take actions that reduce or managed perceived risks. There is evidence from this field of research which suggests that worry drives risk management decisions (Weber, 2006). Hence if a farmer fails to be alarmed about a change in the climate or the risk it poses to them, they shall not take precautions.

How farmers perceive the risk of potential climate change to (their) agricultural productivity plays a significant role when it comes to empirically trying to deduce if farmers have had the foresight and have planned for said potential climate change. Indeed, Shrader (2016) highlights the fact that a significant amount of what is known in terms of climate change impacts on the economy, stems from analysis where the adaptation is *ex post* to experienced weather. Alternatively, if we assume that the economic agent is forward-looking, an *ex ante* adjustment would be made in anticipation of climate change. A recent study by Severen et al.(2016) is firmly grounded on this concept that modern-day farmers take into consideration not only historical and current weather events, but make use of climate projections and other information sets that relay the message of warnings and climate change impacts.

This study contests that within the last thirty years, there has been a distinctive shift in the American agricultural sector, with evidence that farmers have been acknowledging that climate change exists, and is reflected as changes in farmland value. According to the authors, this shift in market behaviors corresponds to the proliferous amount of scientific publications in support of climate change that began in the 1990s, notably with the release of the first Intergovernmental Panel of Climate Change (IPCC) report and usage of the Hadley General Circulation Model (HGCM3). Armed with this new information set, Severen et al. (2016) conclude that since 1987, the farmland market has been capitalizing the farmer's belief that the climate is changing. Such a finding is in stark contrast to the study published the year before by Burke and Emerick (2016). In modeling a farmer's responses to increases in extreme heat over different windows of reactive time, the authors find little evidence of adaptation. Specifically: corn and soy farmers in their study have not been substantially modifying their agricultural production practices in terms of inputs or production.

The capitalization of potential future climate change in agricultural land value relates to a farmer's expectations of whether or not the climate is or will change. With significant levels of uncertainty about climate change, the usage of a Bayesian learning model provides a common foundation for modeling the updating of an individual's beliefs about future climate. As Lybbert et al.(2007) explain, people typically start off with an initial set of beliefs about the likelihood of a specific event occurring. These beliefs are consequently updated when they receive new information pertaining to that event. The power of this learning model resides in its ability to make inferences in the face of uncertainty (Hobbs,1997; Kelly,Kolstad, and Mitchell, 2005; Deryugina, 2013).[11]

Yet for any given event, not all economic agents face the same level of risk and uncertainty. Hirshleifer and Riley(1992) illustrate how the confidence of an economic agent's prior belief can determine whether or not they receive new information in face of this uncertainty, and the impact that this information has on the updating of their beliefs.[12] Specifically, all else equal, the greater the confidence in their prior beliefs, a stochastic shock will be more impactful on their belief updating, relative to individuals who have less confidence in their prior.

The following chapter presents the theoretical model of this study, and clarifies the channels through which these weather shocks might affect farmland values. The model posits that, with regard to their climate priors, farmers are Bayesian in their learning process, and this learning stems primarily from realized weather. Moreover, I show that it is the variance of weather realizations that modulates how long it takes for a farmer to realize that the weather has changed.

[11] Criticisms of the Bayesian learning method with respect to climate change impact literature, include whether or not farmers are myopic, in which case farmers are not Bayesian learners.

[12] Confidence in this context can be understood as the tightness in the prior probability distribution.

CHAPTER 3

THEORY

Capitalization Model

While we cannot directly observe farmer perceptions that the distribution of weather is changing, there are theoretical applications and concepts that can help guide us to develop a proxy to a farmer's behavior. One such approach is to utilize farmer-revealed preferences. These farmer revealed preferences are implicitly embed in observational data.

According to the United States Department of Agriculture (USDA), in recent years, farm real estate (land and structures) has typically accounted for about four-fifths of the total value of U.S. farm assets.[13] This farmland value embodies the discounted future streams of rent from that land, hence reflecting that farmer's expectations of future returns to that land. A change in farmland values is more capable of linking a farmer's changes in behavior to weather than changes in crop yields. Whereby, while the latter can tell us about the biophysical and fiscal damages of yields under varying climate and weather scenarios, the task of disentangling how much of these changes is due to a farmer's perception that the weather is changing, is more complex.

As will be discussed below, by inserting farmland value into a capitalization model, we are able to understand how a change in local weather, a weather shock, will affect

[13]For more details on farmland real estate, see https://www.ers.usda.gov/topics/farm-economy/land-use-land-value-tenure/farmland-value.

that farmland market. This is assuming that weather shock, which is somewhat discontinuous in space, is used as an exogenous source of variation in the farmer's prior belief about the local climate.

To model how a change in weather affects the value of farmland, assume that the quantity of farmland in the United States is fixed, and therefore the maximum price a farmer would be willing to pay for a particular parcel of agricultural land at time i is equal to the summed and discounted expected future stream of earnings from that land (Feichtinger and Salhofer,2011). In other words, farmland value can be written in terms of a capitalization model as:

$$L_{it} = \sum_{t=0}^{\infty} \frac{E[\pi_{it}]}{[1+r]^t} \tag{3.1}$$

where L_{it} represents the value per acre of farmland for farmer i in period t, and is equal to the sum of expected discount future returns, E is the expectations operator conditioned on information available for farmer i at time t, r is the discount rate, and lastly π represents maximum profit. A core component of my research that is not explicitly mentioned in (3.1) is realized weather, which I denote as z_{it}. This random variable is a multidimensional vector of observed temperature and precipitation, and can be defined as $z_{it} = [temperature_{it}, precipitation_{it}]$. Without loss of generality, suppose that weather is drawn from a normal distribution with mean μ and variance σ^2. A key component in determining how farmers process unusual weather events depends on how variable the underlying climatic distribution is. I define a measure of “precision" for observed weather as $\rho = \frac{1}{\sigma^2}$.

Considering that weather is a direct input for agricultural production, I can illustrate a farmer’s expected profit as the optimization problem:

$$\begin{aligned} E[\pi(z_{it}, p_{it}, w_{it}) = \underset{x_{it}, y_{it}}{\text{maximize}} \quad & p_{it} f(x_{it}, z_{it}) - w_{it} x_{it}] \\ \text{subject to} \quad & y_{it} = f(x_{it}, z_{it}) \end{aligned} \tag{3.2}$$

where expected profit for i in time period t consists of three arguments: output prices p_{it}, input prices w_{it}, and observed weather z_{it}, respectively. Similar to Kelly, Kolstad, and Mitchell (2005), I assume that the input and output prices which the farmer faces are not affected by weather and remain constant.[14] The term y represents a vector of agricultural output, while x is a vector of input variables. Notice that production $y_{it} = f(x_{it}, z_{it})$ is a function of inputs and observed weather only, not expectations of weather. Furthermore, the farmer does not believe the distribution of weather has changed relative to the previous time period.

Bayesian Learning Model

Now consider the case where the distribution of weather changes, such that the true mean of weather shifts from $\mu \rightarrow \tilde{\mu}$. To simplify the exposition, I assume that

[14] To be more accurate, the authors state that prices are not affected by a random shock, W_{it}, where W_{it} comes in the form as either a price or technology shock. Given that both W_{it} in Kelly, Kolstad, and Mitchell (2005) and z_{it} in my model are both random variables, the comparison and extrapolation of the effect of shocks on prices is justified.

climate change is affecting the mean weather, not the variance of weather, which the farmer knows, and experiences $z_{it} \sim \mathcal{N}(\tilde{\mu}, \sigma^2)$ each year (Burke and Emerick,2016). Assume that a farmer has a prior belief about the mean weather at any point in time, $\theta(t)$. Let the initial prior θ_0 be based on historical record. Therefore in time period t, farmer i believes that $\mu_{it} \sim \mathcal{N}(\theta_{it}, \frac{1}{\gamma_{it}})$, where γ_{it} represents the farmer's precision (confidence) that $\theta_{it} = \tilde{\mu}_{it}$. If a farmer had full information about the change in climate, then $\gamma_{it} = \infty$ and the farmer's confidence in their prior belief of mean weather would be zero, leading them to quickly adapt.

In reality, however, farmers are likely to update their priors about the climate over time as changing weather patterns are realized, only modifying their behavior after obtaining strong enough information that the climate has changed. For example, suppose that the mean precipitation in May has increased by 4 inches. As the years go by, the farmer gradually changes his estimate of the mean precipitation. However, until the farmer is completely informed of the new precipitation, he will continue to lose profits as a consequence of making sub-optimal input and production decisions (Kelly et al.,1999). To model this change in the farmer's prior, I assume that the farmer follows a Bayesian learning process. This assumption provides us a template to model how economic agents update their beliefs in the face of uncertain events like changes in weather fluctuations.

According to Bayes rule, after the farmer observes $z_{i,t+1}$ (see Cyert and DeGroot 1974; Kelly,Kolstad, and Mitchell, 2005), they will update their prior θ_{it} to generate the posterior $\theta_{i,T}$, where T represents time-periods. This posterior estimate is a weighted average of prior beliefs about mean weather and realized weather.

$$\theta_{i,T} = \frac{\gamma_{it}\theta_{it} + T\rho z_{it}}{\gamma_{it} + T\rho} \tag{3.3}$$

As will be discussed below, the role of a farmer's confidence in their prior belief of the mean weather can have a significant effect on how they react to a weather shock. Consider two farmers who have identical operations, but different observed weather distributions. Let farmer i represent a farmer with a more stable climate regime, in other words a baseline climate that is less variable. Farmer i will perceive a weather shock as a shift in their distribution of weather. In contrast, farmer j, who faces a more variable baseline climate, will consider the shock to be another realization of the current weather distribution and not as a shift.

The weights associated with the farmer's prior and observed weather are γ_{it} and ρ, respectively. The term γ_{it} represents the farmer's confidence that their prior belief of mean is equal to the mean climate $\tilde{\mu}$. In contrast, ρ does not represent a confidence, but the variance of weather events. Note that the denominator in (3.3) represents the posterior precision after T years. According to Meehl et al.(2007), this change in the mean is not accompanied by a change in the variance. Hence, I do not examine the evolution of how a farmer's confidence (γ_{it}) changes over time in the long term. Accordingly, I redefine the farmer's prior belief to be normally distributed and consisting of their prior belief of mean weather and the variance of observed weather, such that $\mu_{it} \sim \mathcal{N}(\theta_{it}, \sigma_i^2)$.

To reflect this updating in (3.3), I can revise expected profit to be equal to:

$$E[\pi(z_{it})] = \int \pi(z_{it}) N(\theta_{it}, \sigma_i^2) dz_{it} \tag{3.4}$$

This formula states that the expected returns from observed weather are equal to the infinitesimal sum of the distribution of weather $\pi(z_{it})$, which represents the monetary value of observed weather, and $N(\theta_{it}, \sigma_i^2)$ which represents the density of the farmer's prior belief of the mean weather.[15]

Connectivity between land value, expected profit, and a farmer's updating of prior beliefs is now hopefully evident to the reader. Taking the derivative of (3.4) with respect to weather and letting λ equal the discount factor of $\frac{1}{(1+r)^t}$, a change in land value after a weather shock can be written as:

$$\frac{\partial \delta L_{it}}{\partial z_{it}} = \delta \int \frac{\partial f(z_i t}{\partial z_{it}} \frac{\partial N(\theta_{it}, \sigma_i^2)}{\partial z_{it}} dz_{it} \tag{3.5}$$

which states that a shock in observed weather leads to a change in land value through a change in discounted expected profit, integrated over all weather outcomes.[16]

[15]The density of a normal distribution for observed weather is:

$$f(z|\mu, \sigma^2) = \frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

,where π does not represent profit, but the numerical value of pi.

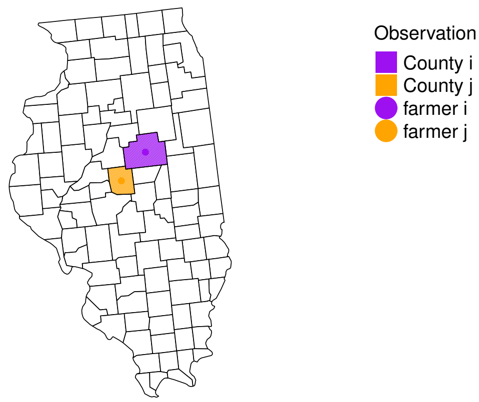
[16]Where a weather shock can be defined as a change in the distribution of observed weather.

A crucial point to highlight in (3.5) is the Bayesian learning process, which is embedded in θ_{it}. For illustrative purposes, let $t = 0$ demarcate the current time period and $t = 1$ represent the time period immediately after a weather shock. Referring to (3), the change in this prior after the weather shock is equal to $\frac{\partial\theta 1}{\partial z} = \frac{\rho}{\gamma_0+\rho}$, which illustrates that the variance of weather modulates how a farmer's prior changes with a shock to weather.

In Figure 3.1, consider farmers in two neighboring counties i and j , where $\rho_{i0} < \rho_{j0}$. After a weather shock, *ceteris paribus*, then in the next time we can expect farmer j to receive a more impactful lesson from this weather shock.[17] Figure 3.2 provides a visual representation to better understand how a greater variance in the weather distribution can influence a farmer's recognition that the climate has changed.

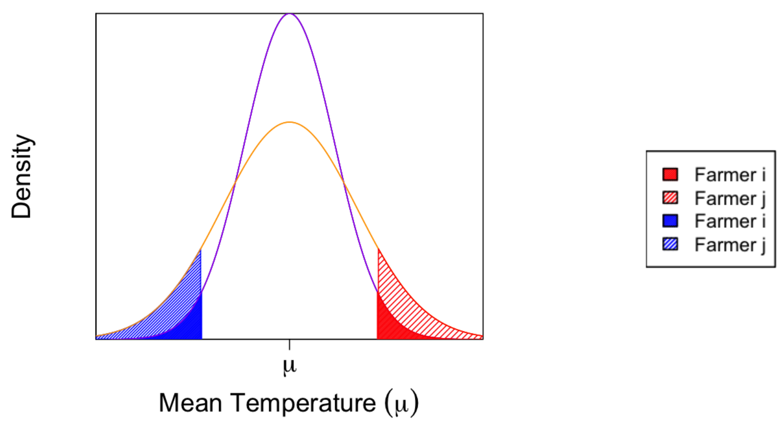
The curves in Figure 3.2 represent two competing states of nature - observed weather for farmer i (in purple) and observed weather for farmer j (in orange), but both experience mean weather centered at μ. The areas shaded in red represent exposure to extreme hot days, whereas the areas shaded in blue represent exposure to extreme cold days. The density of exposure to these extreme days is greater for farmer j than for neighboring farmer i. As such, after a weather shock, the type I and type II errors for farmer j are larger than the corresponding errors belonging to farmer i in part because of farmer j's larger weather variance. This translates into larger adjustment costs for farmer j. In the next section, I discuss my empirical approach.

[17]Of course, one also needs to consider where on the distribution farmer *i(j)* are. If they are at or near the plateau, where there is little to no variance, then the Bayesian updating lesson is not applicable.



Notes: This map illustrates farmers in neighboring counties. Farmer i is in the county shaded purple, whereas farmer j is in the county shaded in orange. Note that empirical analysis is not restricted to this sample area, which represents Illinois. The plotting of these observations is purely for theoretical and illustrative purposes of neighboring farmers.

Figure 3.1: Neighboring Farmers



Notes: This figure identifies how two farmers with different baseline climates, have different exposures to extreme hot (shaded in red) and extreme cold (shaded in blue) days. Notice that exposure to extreme days for farmer j is actually the combination of the two textures of the same color.

Figure 3.2: Theoretical Distributions for Two Farmers with Different Variances of Weather Realizations

CHAPTER 4

EMPIRICAL APPROACH

The main objective of this thesis is to detect if weather shocks in the United States have been capitalized into the farmland market. To translate my research question and theoretical model into an empirical application, I elect to utilize weather variation in a panel data setting across time to estimate the sensitivity of weather effects on farmland value. A distinctive advantage of using a panel method is that year-to-year variations in weather are plausibly random to farmers. By utilizing exogenous (yearly) variation in weather outcomes over a fixed location, a panel model can causatively identify effects of said weather variables on outcomes like farmland value.

Utilizing Degree Days to Capture Nonlinearities

Determining how to model the relationship between weather and our dependent variable - farmland value - is a critically important next step. Correct specification of the relationship between weather and land value is essential before more elaborate models can be used to examine if weather shocks have a transient or permanent impact on the dependent variable. Recent literature on the economic impacts of climate change has often found a nonlinear relationship between weather and economic outcomes that include agricultural yields, with extremely warm temperatures being especially important (Aufhammer et al., 2013). I utilize degree days to capture this nonlinearity.

Agronomists have shown that plant growth depends on the cumulative exposure to heat and precipitation during the growing season (Deschênes and Greenstone, 2007). There is a threshold of temperatures - an upper and lower bounds- which crops can absorb heat and benefit. Exceeding this upper bound has adverse impacts on both the crop's yield and health. I follow the standard method to capture this nonlinearity by utilizing degree days: the amount of time a crop spends between its upper and lower bounds.

Degree days are typically assigned to one of two categories: normal degree days (which fall between the range of that crop's upper and lower bounds), and harmful degree days, temperatures which exceed the upper bounds. Given that the upper thresholds for the three most important cash crops of corn,soy, and cotton have upper temperature bounds of 29°C, 30°C, and 32°C, two common combinations of degree day assignments are 1) degree days $10-30°C$ with harmful degree days equal to above 30°C, and 2) degree days $8-32°C$ and harmful degree days of degree days above 32°C. I test the sensitivity of the temperature effect on land value by employing both of these alternative degree day specifications.

Baseline Model

To analyze the effects of weather shocks on the farmland market, two separate models will be used.

First, a simple OLS regression that exploits random variation in yearly weather observations is as follows:

$$y_{it} = \alpha_i + \tau_t + z_{it} + p_{it} + p_{it}^2 + \epsilon_{it} \tag{4.1}$$

where y_{it}, is the natural log of farmland value for a county i in time period t. The terms α_i and τ_t represent county effect and time effects, respectively. Whereas the county effect will absorb any fixed spatial, time-invariant characteristics (such as soil quality), the time effect will neutralize any common shocks and thus help ensure that relationships of interest are identified from idiosyncratic local shocks. It should be noted that while year and location fixed effects may capture all time-invariant and time-varying confounding factors, a large amount of variation is also captured and hence amplifies measurement error. The error term ϵ_{it} , allows for spatial correlation to occur within each year through a semi-parametric procedure first utilized by Conley (1999). The term z_{it} represents temperature realizations while the two terms p_{it} and p_{it}^2 represent precipitation and quadratic precipitation for the growing season. Aufhammer et al.(2013) emphasize that because precipitation and temperature are often correlated, the coefficient on precipitation will measure the combined effect of the two weather variables on a model's dependent variable. Hence, in order to obtain unbiased estimates of marginal effects of precipitation and temperature on farmland value, both must be include in our regression.

Elaboration upon how standard errors are corrected for spatial correlation is warranted. Anselin (1988) shows how the presence of spatial dependency in the data will create biased and inconsistent OLS estimators. This study contains weather data, whose variation is often considered random over time, but not over space. Without knowing the extent and type of residual spatial dependence, I opt to use the semi-parametric procedure first exercised by Conley (1999), which does not require a weighting matrix to be specified. By applying these Conley standard errors, we are assuming that as the geographic distance between observations increases, the spatial correlation of the model errors shall decay. Hence, correcting for spatial spatial correlation avoids the empirical sand trap of conducting statistical inferences on undersized standard errors. As a check, I calculate an alternative to Conley Standard Errors, and cluster errors by state and year.[18] We can rewrite (4.1) as:

$$y_{it} = \alpha_i + \tau_t + \sum \theta_i f_i(W_{it}) + \epsilon_{st} \tag{4.2}$$

where θ_i is the coefficient for our yearly weather variables, W_{it}. Because we are using yearly variations in weather, I presume that this variation is orthogonal to unobserved determinants of agricultural outcome, like soil quality, hence providing us with a potential solution to the omitted variable bias. In other words, I make the following assumption:

$$E[f_i(W_{it}\epsilon_{st}|\alpha_i, \tau_t)] = 0 \tag{4.3}$$

[18]It is common practice for the empiricist to cluster at large spatial scales when geographically based correlation is present.

Distributed Lag Model

Thus far we have only been considering contemporaneous weather data. But what if the effect of weather on farmland value that we are seeing today is not based solely on this year's weather events, but an accumulation of previous year's weather events too? Without the inclusion of lagged weather variables, one might incorrectly conclude that a regression's outcome is a permanent effect instead of a transient one. To investigate if the baseline model's results represent permanent or temporary effects, a finite distributed lag model is estimated where:

$$y_{it} = \alpha_i + \tau_t + \sum_{n=0}^{n=N} \beta_n X'_{i,t-n} + \epsilon_{st} \tag{4.4}$$

where y_{it} represents the value of agricultural land per acre in county i for year t. The term $X'_{i,t-n}$ is a vector of temperature and quadratic precipitation realizations. The term α_i represents a full set of county fixed effects, whereas the term τ_t identifies the year effect. Notice the n subscript for the $X'_{i,t-n}$ vector, where n=N represents the total number of lags considered. By looking at a number of lagged weather variables, we can determine if changes in farmland value over time is a function of current and past weather events $X'_{it}, X'_{i,t-1}, ...X'_{i,t-n}$, where the last term $X'_{i,t-n}$ indicates that after N lags, the effect of previous weather events on current land and building values has been exhausted. It is often a concern that X'_{it} and $X'_{i,t-1}$, along with all other pairs of lags will be highly collinear. However, because weather fluctuations are considered random at a specific location, and tend not to be serially correlated in consecutive years, I believe the concern of collinearity is mitigated. This is assuming that the number of lags have been correctly specified. If they have been misspecified, then the lag distribution will be inaccurate and the cumulative impact of Degree Days on land values will be biased.[19] The exhaustion of this effect is econometrically tested through a joint-hypothesis F-test, whereby if $\sum_{n=0}^{N} \beta_0 + \beta_1 + ... \beta_N \neq 0$, the effect is a permanent, as opposed to a transitory one.

Stability

A passage from Hsiang (2016) exemplifies why it is important to investigate across subsamples of time and space for the stability and sensitivity of the temperature-farmland value relationship.

> *In many contexts, it is plausible that climatic events at moments in the past or at nearby locations affect an outcome at a specific time and place, much like the surface of a pond observed at any moment and location might depend on whether a raindrop disturbed that location moments before, or a nearby point on the pond surface?*

The intuition of comparing empirical results by stratifying observations on temporal and geographic divisions, such as years and geographic coordinates, allows the researcher to investigate if the overall regression results are uniformly experienced

[19]Following the literature, I choose to determine lag length by sequentially adding lagged weather variables until the latest addition is no longer statistically significant.

or if particular subsets experience different marginal impacts. This is achieved by conducting a Wald test to determine whether all coefficients for subgroups are jointly the same.

Stability Across Space

To examine the sensitivity of the temperature effect on farmland, I adopt two methods to spatially separate the study area. The first method divides the sample into two equally sized, and mutually exclusive regions of East and West or North and South, using the study's median latitude and longitude observations to segment the regions. Recall the theoretical assertion that all things considered, a farmer with a more variable baseline climate, will update their beliefs of climate norms more slowly than a farmer who has a less variable baseline climate. To reflect this hypothesis, the second division is made by separating counties based on the coefficient of variation for harmful degree days.

Stability Across Time

The premise that there has been a shift in the farmer's belief about climate change over the last thirty years is an empirical foundation that Severen et al.(2016) promote. In part due to the proliferate amount of climate information that has become available since the 1990s, they conclude that farmers are indeed capitalizing climate change into farmland value. However, whereas the authors examine the evolution of climate change beliefs in the cross-section, I am motivated to examine this relationship with a panel model, and to see if there has been a structural shift in the farmland market. To that extent, I divide the sample into two equally-sized year groups of 1950-1978 and 1982-2012.

CHAPTER 5

DATA AND SUMMARY STATISTICS

Sample Determination

In the agricultural economic literature, development pressure and agricultural irrigation are recognized to be two potentially important determinants of farmland value. As such, following Schlenker and Roberts (2006), Figure 5.1 displays a map of my sample area, where counties in the contiguous United States were omitted if they can be classified to be irrigated or urban.[20] A brief overview of what constitutes urban and irrigated counties in this study is provided below.

The influence of irrigation

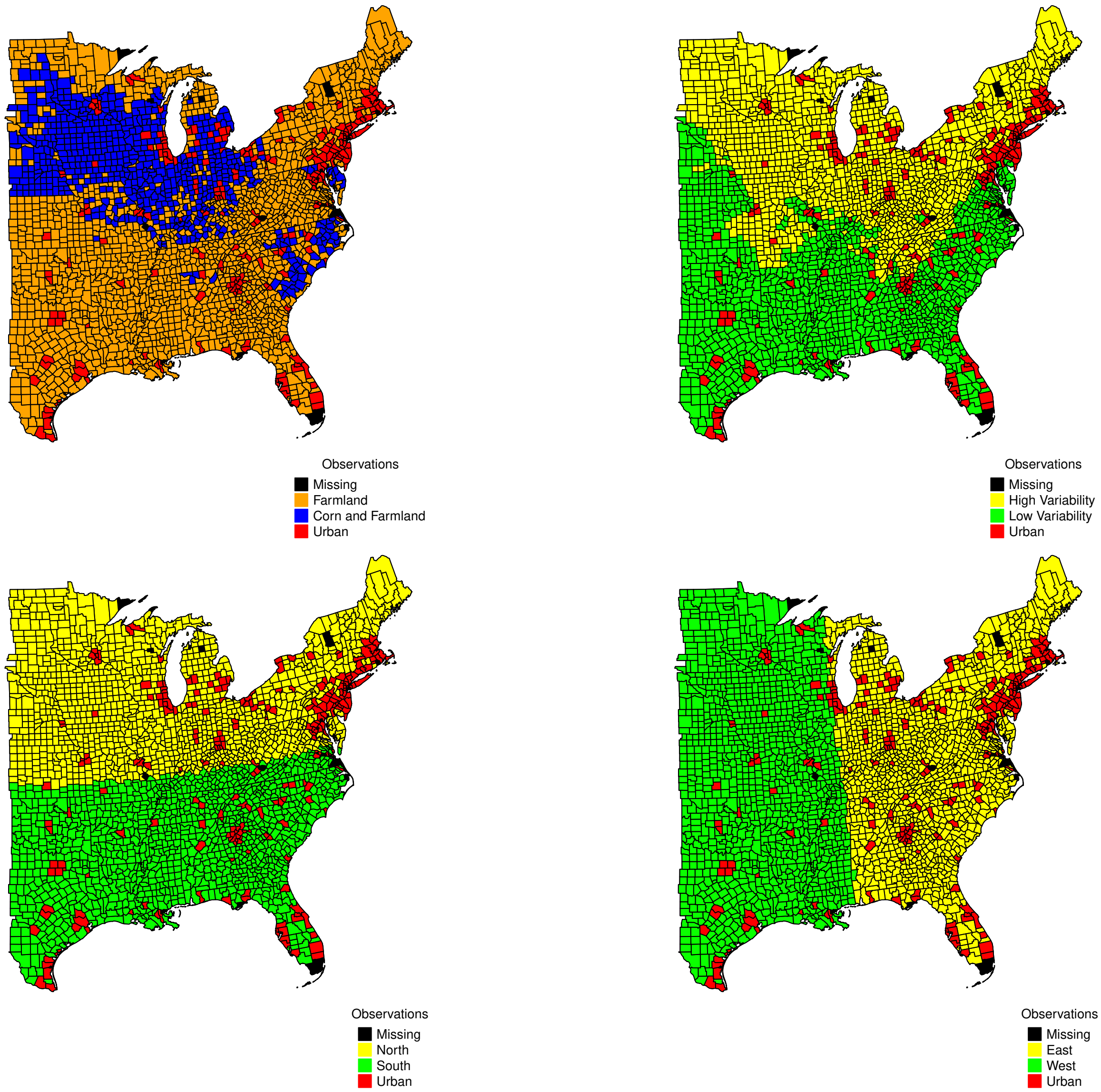
It is widely known that a majority of U.S. crops require at least 20 inches of water a year to grow. In the contiguous United States, a distinctive geographic boundary exists to delineate regions that do and do not receive this minimum requirement: the 100$^{\text{th}}$ meridian. Commonly referred to as the "rainline", agriculture is able to occur without supplementary irrigation water to the right (east), whereas to the west (left) it generally cannot. In irrigated farmland areas, precipitation is complimented by irrigated water, whose infrastructure in some cases is heavily subsidized by the US government. Hence, the usage of irrigated water for farming operations severs the direct connection between that farmer's current climate, specifically precipitation and

[20]In Figure A1, a comparison of regions for CV30 and CV32 is presented.

temperature, and farm-level economic outcome. Were we to combine these counties together into one sample, and not treat the price of water differently, the result would be biased regression coefficients of our weather variables.

The influence of urbanization

Noting that land prices reflect not only the current uses of land, but potential uses as well, Plantinga et al.(2002) find that over 80 percent of farmland value close to New York City is attributable to the option value of developing land for urban uses. Hence, the impact of weather shocks and climate change will likely have a different effect on urban land prices and surrounding farmland, than rural areas. Following the literature, a county is considered to be urban if it has population density greater than 400 persons per square mile. This panel of data consists of county level observations in the contiguous United States from 1950 to 2012. All monetary values are expressed in constant 2012 United States Dollars (USD) using the GDP implicit price deflator. In the remainder of this chapter, the three families of data types - weather and climate, agricultural, and socio-economic - are discussed.



Notes: This figure identifies the parent dataset in the upper left-hand panel. Farmland counties are the combined orange and blue counties, and is a panel of N=2,193 and T=14. The corn counties are in blue, with N=631 and T=63. The upper right-hand panel corresponds to the geographic division of areas into high and low climate variability, based on the Coefficient of Variation for Degree Days $> 30°C$. The lower panels show the geographic subsamples into North-South divisions (left) and East-West divisions (right). Counties in red are urban, while counties in black are missing.

Figure 5.1: Parent Dataset and Regional Divisions

Description of Data Sources

Table 5.1 provides a summary of the data sets used in this study. This includes the time periods they correspond to , the unit of observation (referred to as resolution below), and their source. While the frequency of observations for crop yields, value of farmlands and buildings, and population census is not explicitly stated in the table, we do describe this in their respective data descriptions. Furthermore, it should be noted that the crop yield data corresponds to corn yields harvested for grain.

Weather and Climate Data

The weather and climate data come from two sources. The primary dataset is from Schlenker and Roberts (2009), and consists of interpolated monthly mean, maximum, and minimum temperature and precipitation amounts for 2.5×2.5-mile grid cells across the contiguous United States from 1950 to 2005. The climate and weather data for the remaining years of this study (2006-2012) are from PRISM .

PRISM datasets are widely considered to be one of the most well regarded and reliable interpolation procedures for climate data on a small scale (Schlenker and Roberts, 2006; Deschênes and Greenstone, 2007). However, because the underlying climate data is gridded, it needs to be aggregated to the county level in order to match with agricultural areas. This is accomplished by Ortiz-Bobea (2016) , by weighting each native PRISM grid by the amount of cropland it contains based on

Table 5.1: Variables and Data Sources

Variable	Time Period	Resolution	Source
Agriculture			
Farmland Value and Farmland Acres	1950, 1954, 1959, 1964, 1968, 1974, 1978, 1982, 1987, 1992, 1997, 2002, 2007, 2012	County	Haines et al (2012)
Crop Yields (Corn)	1950-2012	County	USDA Quik Stats
Non-Irrigated Cropland Cash Rent	2009-2014	County	USDA Quik Stats
Climate			
Daily minimum and maximum temperature	1950-1980	4km	Schlenker & Roberts(2009)
Monthly avg. temperature and precipitation	1981-2012	4km	PRISM
Cropland Weights	2008-2014	30m	USDA CDL
Controls			
Population	1970-2012	County	US Census
	1950,1960	County	Haines et al (2012)

Notes: The frequency of observations is not explicitly stated in the table above for the following: Farmland Value (4-5 years);Population Census(decadal); Crop Yields(yearly); Cropland Weights(yearly). Observations are restricted to east of the 100$^{\text{th}}$ meridian and non-urban counties (population density less than 400 persons per square mile).

the USDA Cropland Data Layer. The Cropland Data Layer (CDL) provides 30 meter resolution land cover pixels, which correspond to over 100 land classifications. The weights are based on cropland pixel counts falling within each PRISM data grid. The average of the CDL cropland counts for years 2008-2014 were used.[21]

[21] An alternative method to identify agricultural area is done by Schlenker,Hanemann and Fisher (2006), who derive farmland area from the 1992 National Land Cover Characterization by the USGS. This land classification is based on Landsat satellite images and assigns each pixel to one of several land classifications, cropland and pasture being two of them. Therefore, there is relatively little difference between cropland, and cropland and pasture weights in the eastern US, due in

Agricultural Data

The agricultural data for this study come from two sources: Haines, Fishback, and Rhode (2012), and the United States Department of Agriculture National Agricultural Statistics Service. The data from Haines, Fishback and Rhodes (2012), is a collection of US Census of Agriculture data, whereas the NASS data used in this study consists of a 63-year panel (1950-2012) of corn yields.

The USDA Agricultural Census dataset provides a comprehensive overview of the number, types, output, and prices of various agricultural products, as well as information on the amount, expenses, sales, values, and production of machinery. The surveyed population are operators of farms and ranches who have sold at least $1,000 of agricultural products during that census year. There are a total of fourteen agricultural censuses (beginning with the 1950 and ending with the 2012 agricultural census) included in this analysis. The number of eastern non-urban counties with non-missing farmland data is equal to 2,193 for all census years.

The primary dependent variable used in this study is the value of land and buildings ($ USD per acre), which is obtained by asking farmers their estimate of the current market value of their land and buildings.[22] The other agricultural variables included in this study are farmland acres, irrigated cropland acres, and number of farms. Like

part to the fact there is not a significant amount of pasture in this region. A problem with pasture classification relates to the analyst's difficulty to distinguish LandSat or other satellite imagery into actual pastureland or natural grassland (A.Ortiz-Bobea, personal communication, December 21,2016).

[22]As discussed in the econometric results chapter, I perform a falsification test post-estimation of the distributed lag model, by substituting corn yield as the dependent variable.

MNS (1994), I interpret the value of land and buildings to be a proxy of farmland value.

Chay and Greenstone (2005) raise some concerns about the usage of county-level data in a hedonic methods study. These include, first, the inability to measure within-county heterogeneity with respect to qualifying factors (in my case, land quality and other land attributes). Second, as originally conceived, the hedonic method was meant to be an individual-level model. Therefore, an aggregation to the county-level may induce some bias. But like Chay and Greenstone (2005), I suspect that the aggregation to the county level will not be an important source of bias.

Socio-Economic Data

In previous studies, population density has been shown to significantly affect farmland value (Roberts and Schlenker, 2011). As such, counties exceeding a certain population or population density are excluded, in an effort to capture the influence of population pressure on farmland value. County level population data comes from both the United States Census and Intercensal Estimates. However, these data are only available between 1970 and 2012. Consequently, the remaining population data is obtained from Haines, Fishback, and Rhodes (2012). Because intercensal estimates before 1970 are not available, county populations for study years are interpolated between decennial censuses using a natural spline.

Summary Statistics

Table 5.2 provides a snapshot of our panel of data, highlighting the summary statistics of agricultural and weather variables.

Table 5.2: Agricultural and Climate Variable Summary Statistics

Variable	μ	min	max	σ
Farmland Value	1,755.35	50.39	21,807.05	1,325.92
Farmland Acres	240.38	0	217.6	181.5
Degree Days $8 - 32°C$	2,192.43	928.4	3,160.65	349.62
Degree Days $10 - 30°C$	1,652.06	686.5	2,234.35	230.69
Degree Days $> 30°C$	70.43	0	498.62	66.82
Degree Days $> 32°C$	31.36	0	325.8	39.2
Precipitation	581.52	166.44	1,398.75	149.74

Notes: Values are county averages of a balanced farmland panel, where N=2,193 and T=14, east of the 100^{th} meridian. Counties were omitted if their population density was greater than 400 persons per square mile. The growing season is April through September. Farmland Value is reported in constant 2012 USD, Farmland Acres are in thousands of acres, and Precipitation is reported in millimeters.

Table 5.3: Averages of Climate Variables and
Farmland Value Over Time

Variable	Sample	Early	Late
Farmland Value	1,755.35	1,201.43	2,309.27
	[816.36]	[624.77]	[1,106.92]
Farmland Acres	240.38	261.26	219.50
	[177.36]	[177.93]	[178.71]
Precipitation	581.52	593.31	569.73
	[99.55]	[107.66]	[97.98]
Degree Days $8-32°C$	2,192.43	2,180.31	2,204.55
	[333.46]	[336.69]	[331.82]
Degree Days $10-30°C$	1,652.06	1,643.44	1,660.68
	[216.74]	[222.26]	[212.54]
Degree Days > 32°C	31.36	34.63	28.09
	[31.06]	[36.51]	[26.05]
Degree Days > 30°C	70.43	74.66	66.20
	[56.93]	[63.54]	[50.85]

Notes: Averages and standard deviations (in brackets) are reported for agricultural and climate variables. Note that the column Early corresponds to sample averages for 1950-1978, while the column Late corresponds to sample averages for 1982-2012.

Tables 5.3 above, and Table 5.4 on the following page, provide a disaggregation of these summary statistics across time and space, respectively.[23] Throughout this thesis, I refer to two groupings of weather variables : primary climate variables and alternative climate variables. Primary climate variables consists of Degree Days $10-30°C$, Degree Days > 30°C, Precipitation, and Precipitation^2. Alternative Climate variables include Degree Days $8-32°C$ and Degree Days > 32°C.

[23]Summary Statistics for corn yields is in found in Table A1.

Table 5.4: Regional Averages of Farmland Real Estate and Climate Variables

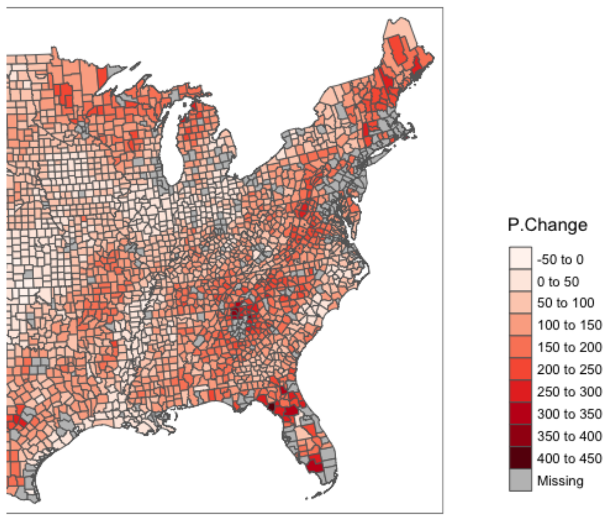
Variable	North	South	East	West	High	Low
Farmland Value	1,929.20	1,581.65	1,986.24	1,524.66	1,934.78	1,576.08
	[938.85]	[625.56]	[832.06]	[730.86]	[887.63]	[693.44]
Farmland Acres	265.54	215.25	146.16	334.52	214.94	265.80
	[178.66]	[172.44]	[89.85]	[192.57]	[136.79]	[207.12]
Precipitation	537.29	625.71	599.66	563.40	569.03	594.00
	[72.23]	[103.33]	[91.85]	[103.56]	[66.15]	[122.99]
Degree Days $8 - 32°C$	1,935.86	2,448.76	2,203.56	2,181.31	2,007.60	2,377.09
	[255.22]	[160.40]	[343.63]	[322.60]	[289.17]	[265.54]
Degree Days $10 - 30°C$	1,490.53	1,813.45	1,668.31	1,635.82	1,546.94	1,757.08
	[185.25]	[86.64]	[221.08]	[211.08]	[207.18]	[170.17]
Degree Days > 32°C	13.47	49.23	18.98	43.73	12.91	49.79
	[14.57]	[32.82]	[16.89]	[36.57]	[13.58]	[32.63]
Degree Days > 30°C	33.11	107.71	50.67	90.17	33.25	107.57
	[26.84]	[54.56]	[39.92]	[64.08]	[27.00]	[54.68]

Notes: Columns 2 through 4 correspond to geographic subdivisions of cardinal regions, as described in Chapter 4, each of which is N=15,351. The last two columns correspond to regions of high and low climate variability, when the sample is divided by the Coefficient of Variation for D.Days > 30°C. Standard deviations are in brackets. All dollar values are in constant 2012 USD. Farmland acres are reported in thousands of acres (e.g. the Northern average of 265.54 = 265,540 acres).

Figure 5.2 on the following page refers to the change in farmland value in the sample area between 1950 and 2012. This change is equal to the difference between two period averages (average farmland value for 1950-1978 and average farmland value for 1982-2012), for each county. What is particularly interesting of this image is the fact that farmland value has not appreciated as largely in the Cornbelt or Mississippi Delta in comparison to other regions of the country.[24] These two areas represent some of the greatest and most productive agricultural farmland in the country. Indeed, the greatest appreciation occurs in the Mid-Atlantic corridor, the Northeastern corridor and the Great Lakes region, which suggests that changes in farmland value may not be driven by weather shocks.

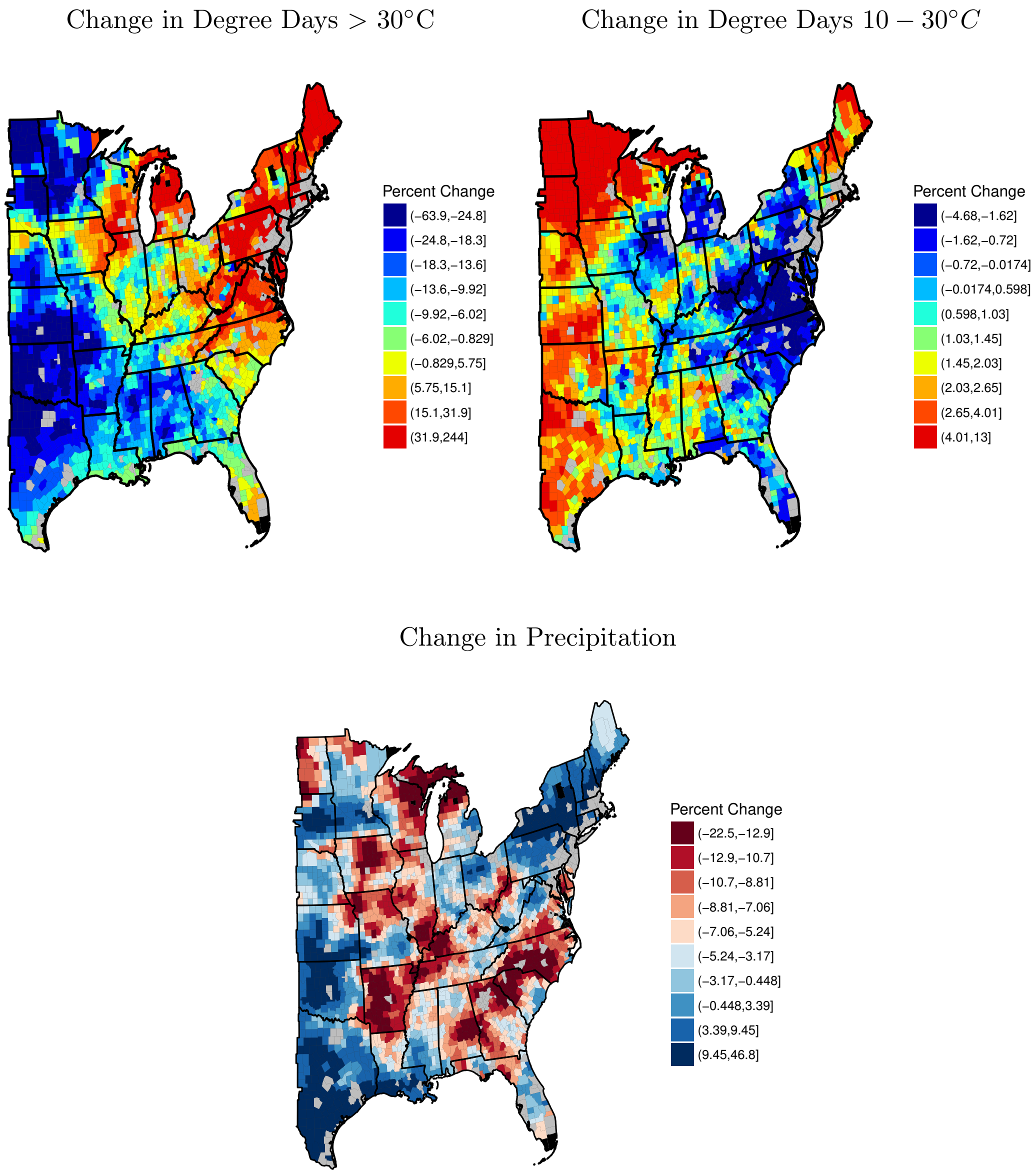
[24]To designate these regions, I refer to the Farm Production Regions, constructed by the USDA Economic Research Service, whereby the Cornbelt consists of Illinois,Indiana,Iowa,Missouri and Ohio. The Mississippi Delta consists of member states Arkansas,Louisiana, and Mississippi. A map of Farm Production Regions may be found at http://www.nrcs.usda.gov.

Percentage Change in Farmland Value Over Sample Period



Notes: Counties shaded in grey are missing or urban.

Figure 5.2: Change in Farmland Value



Notes: The above figures correspond to the changes in the study's main climate variables between two periods (1950-1978) and (1982-2012). Scales are in percentage change. The growing season is April to September. Counties shaded in grey are urban. Counties shaded in black are missing.

Figure 5.3: Change in Primary Climate Variables

CHAPTER 6

EMPIRICAL RESULTS

The narrative of this chapter is as follows. I first discuss the results of the baseline regression, which provides motivation to investigate the sensitivity of weather shocks on changes in farmland value across time and space. Next, I present findings of the baseline model when divided into geographic subsamples. This is followed by investigating the stability of the baseline model across two equally sized time periods. Lastly, a placebo test is paired with the distributed lag model to examine if the the results from the sample-wide regression are spurious.

Baseline Model Results

The main set of regressions in this study include the usage of normal degree days and harmful growing season degree days to model the relationship between temperature and farmland value. Specifically, I follow the literature and utilize the tandem of normal degree days with upper and lower thresholds of degree days $10-29°C$ and harmful degree days as the aggregate of degree days over 30°C.

The OLS results of the baseline model (4.1), are presented in Table 6.1.[25] None of the four weather variables are distinguishably different from zero. Two sets of standard errors are located under each regression coefficient. The na standard errors are in parentheses, and have not been corrected for heteroskedasticity or spatial correlation.

[25]In Table A4, I rerun (4.1) but include Conley standard errors instead of naive ones. This table indicates that clustered standard errors are at least four times as large as Conley standard errors.

In brackets, are multiway clustered errors at the state and year level. This latter set corrects for heteroskedasticity and spatial correlation, and will be reported in all models, unless stated elsewise. A brief justification of multiway clustering is provided below.

Table 6.1: Baseline Regression Results

	Dependent variable:
	Log Farmland Value
Degree Days $10 - 30°C$	-25.92 (2.94) [37.28]
Degree Days > 30°C	-20.86 (8.09) [94.10]
Precipitation	8.22 (4.08) [25.92]
Precipitation^2	-0.03 (0.01) [0.08]
Observations	30,702
R^2	0.003417

Notes: The above table corresponds to a model for panel data of farmland values, where N = 2,193 and T = 14 census years (1950-2012). There are two sets of standard errors reported under the regression coefficient. The untreated, naive standard errors are in parentheses. In brackets are standard errors which have been clustered by state and year. The model includes county and year fixed effects. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

A popular approach for allowing spatial correlation in the disturbance is the semi-parametric routine developed by Conley(1999), whereby, as physical distance between neighboring observations increases, the spatial dependence between those observations will decay. Figure 6.1 highlights that when treated for spatial correlation, the standard errors for farmland value (left pane) do not increase in magnitude as one might expect. While surprising, it is not necessarily a call for alarm.[26]

As a check, I compare the accuracy of these standard errors by re-running (4.1) with corn yields as the dependent variable. The plots of these standard errors for corn yields are in the right panel in Figure 6.1. While it is clearly evident that standard errors are increasing with distance for each dependent variable in Figure 6.1, that I find similarly small standard errors for the corn yield model is an indicator that there is some behind the scenes issue with the calculation. I therefore cluster at the state and year level to account for spatial correlation and heteroskedasticity.

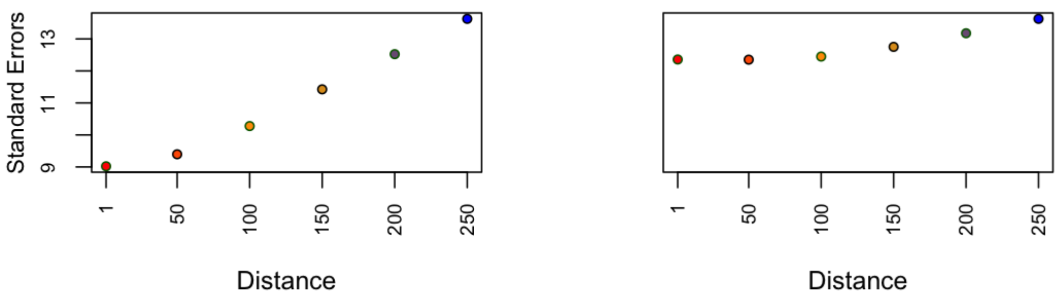
Stability Across Space

Division into Cardinal Directions

To verify if the effect of these weather fluctuations on changes in farmland value are stable across space, I first divide my study area into cardinal directions of East, North, South, and West, and re-estimate the baseline line model. Separation into these four regions was motivated by the clear trend in temperatures cooling from south to north, and a markedly distinct pattern in increasing growing precipitation from West to East, as evidenced in Figures A4 through A6, which illustrate regional

[26]Conley 1999 shows that while standard errors treated for spatial correlation are, in general, as large as standard errors that are IID or heteroskedastically consistent, they can also be smaller due to their fact their asymptotic variances are smaller within spatial data.

differences in exposure to Degree Days $> 30°$C, Degree Days$10 - 30°C$, and growing season precipitation.



Notes: These standard error plots correspond to harmful degree days for farmland values (left) and corn yields (right), from 1950-2012. The routine used to treat for spatial correlation is adopted from Conley (1999). Distance is measured in miles. To interpret standard errors, the reader should divide the value by 100,000.

Figure 6.1: Evolution of Conley Standard Errors for Two Dependent Variables

As a check, I compare the accuracy of these standard errors by re-running (4.1) with corn yields as the dependent variable. The plots of these standard errors for corn yields are in the right panel in Figure 6.1. While it is clearly evident that standard errors are increasing with distance for each dependent variable in Figure 6.1, that I find similarly small standard errors for the corn yield model is an indicator that there is some behind the scenes issue with the calculation. I therefore cluster at the state and year level to account for spatial correlation and heteroskedasticity.

Table 6.2 presents the results of the baseline regression when we include an interaction of a regional dummy with the four weather variables. In Column A, (4.1) is interacted with regional dummy East-West, whereas in Column B, our baseline model is interacted with regional dummy North-South. As evidenced in Column B, the baseline model results appear to be sensitive to regional divisions, whereby, while no weather variables are statistically indistinguishable from zero in Column A, both precipitation terms for the southern region are highly significant, and with the expected sign in Column B. Additionally, the R^2 terms in both models has significantly increased from the baseline comparison: rising from 0.003 to 0.021 in the North-South regression, and 0.011 in the East-West regression.

A possible explanation as to why the weather coefficients are not jointly different in the East-West separation could be attributed in part to the comparatively similar temperature exposures, in comparison to the North-South division. While temperature has often been attributed as the stronger of the two drivers in climate change, and given that the noticeable difference in East-West is precipitation, it could be that because there is relatively more irrigated land in the western half of the sample, hence the two regions experience the same effect of weather shocks on changes in farmland value. Alternatively, because precipitation events tend to occur on a smaller spatial scale than are generally measured, there is higher likelihood that this weather variable is suffering from measurement error.

Table 6.2: Baseline Regression Results by Cardinal Direction

	East-West		North-South	
	East	West	North	South
Degree Days $10-30°C$	-25.43	-43.99	-21.55	-30.91
	[37.42]	[46.39]	[38.91]	[38.33]
Degree Days $> 30°$C	-171.40	-6.80	-145.57	-103.88
	[156.84]	[115.67]	[148.42]	[86.74]
Precipitation	-19.40	24.06	70.58	-58.68***
	[42.42]	[30.90]	[48.10]	[15.78]
Precipitation^2	0.000,2	-0.03	-0.20	0.14***
	[0.11]	[0.10]	[0.19]	[0.03]
Wald Test of Joint Significance (p-value)	0.392	0.392	0.001***	0.001***
Number of Weather Variables Individually Different at p=0.05	1	1	3	3
Observations	15,351	15,351	15,351	15,351
R^2	0.01143	0.01143	0.02084	0.02084

Notes: The above table corresponds to the baseline model when divided into regions of East versus West, and North *versus* South. In brackets are standard errors which have been clustered by state and year. The number of weather variables across regional pairings is reported on the last line. A value of 3 indicates that 3 out of the 4 weather variables were individually different at the $p = 0.05$ level. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

Division into High and Low Climate Variability

This study's interest in examining if farmers are capitalizing expectations of recent weather shocks can be dissected even finer: of chief interest is the modeling and understanding how this group of stakeholders reacts to harmful degree days. Instead of dividing the sample into groups based on their geographical location, I separate the study area into different regions based on the variability of a climate variable: harmful degree days. To model this climate variability, I elect to calculate the coefficient of variation for the aforementioned variable, which is the ratio of the standard deviation to the mean. This calculation allows us to map the yearly fluctuation in harmful degree days, and has a straightforward interpretation : the higher the coefficient of variation, the larger the yearly fluctuations in the variable of interest, which translates into a less stable and less predictable climate.

A caveat to modeling climate variability on a single parameter is intuitive : by deciding to divide the sample along the coefficient of variation for harmful degree days, one could argue that a disproportionate weight is being assigned to this one measure of variability. An alternative would be to consider the coefficients of each of our weather variables in union, and divide the sample based on counties that overlap. Yet a quick glance at the three coefficients of variation of our primary weather variables, as found in Figure A2, reveals that the counties in common are not so clearly distinguished. Hence, I divide by the CV of harmful degree days, with the aim of examining how farmers across space react to weather shocks when they have varying baseline climates. A visual representation of the high and low variability climates is presented in Figure A9, and reveals that the more variable climate is relatively parabolic, whereas the more stable region for harmful degree days is primarily in the southern half of the study site.

Table 6.3 presents the result of the baseline regression model when the weather variables are interacted with a coefficient of variation for harmful degree days dummy. Linear and quadratic precipitation terms are statistically significant and have the expected sign. However, whereas these terms were statistically significant in the Southern region in Table 6.2, they are now statistically significant for the less stable. A single weather variable, normal degree days, is statistically significant in the more stable region. A Wald test rejects the null hypothesis that the weather coefficients for these two regions are jointly the same, which provides supporting, though not absolute, evidence that how variable of a climate a farmer lives in plays a role in their capitalization of weather shocks.

Testing Over Time

I now turn towards investigating the sensitivity of the baseline model to equally long and mutually exclusive time period of 1950-1978 and 1982-2012. Technological improvements over the past 30 years have resulted in crop yields in American agriculture significantly increasing. For instance, the corn yield sample used in this study has experienced average yields increase on the order of 1.75 times.[27] Considering this

[27] Average corn yields for 1950-1981 were 69.5 bushels per acre, whereas averages for 1982-2012 were 122.2 bushels per acre.

Table 6.3: Baseline Regression Results by Climate Variability

	Climate Variability	
	High	Low
Degree Days $10-30°C$	-14.62	-48.25*
	[38.26]	[34.36]
Degree Days > 30°C	17.68	-71.81
	[92.56]	[90.73]
Precipitation	68.22**	-23.70
	[36.59]	[23.96]
Precipitation^2	-0.26**	0.08
	[0.13]	[0.05]
Wald Test of Joint Significance (p-value)	0.002**	0.002**
Number of Weather Variables Individually Different at p=0.05	3	3
Observations	15,351	15,351
R^2	0.01003	0.01003

Notes: The above table corresponds to the baseline model when divided into regions of high and low climate variability for CV of harmful degree days. In brackets are standard errors which have been clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

statistic, advances in agricultural infrastructure, and the continuous development and implementation of new government policies , it is a curious intrigue to examine if weather shocks have had similar effects on the change in farmland value across time. Figure A10 displays the mean climate for the study's early and late periods.[28]

Table 6.4 highlights that no weather variables across time are statistically indistinguishable from zero. A Wald test for joint significance concludes that these two subsamples of time are not jointly different from each other, and all pairwise tests of equality fail to reject the null hypothesis that they are equal. As a side note: it would be interesting to take this finding and investigate if, when I introduce climate variables in an alternative model, those results support those of Severen et al.(2016), who have concluded that since 1987, there has been a structural shift in the farmland market and farmers are capitalizing their beliefs of climate change.

Distributed Lag Model

Thus far, the narrative of my empirical results reflects weather shocks and changes in farmland value over current weather for each census year. This implicitly assumes that, for each respective census year, farmers did not consider past or future weather events to play any role in their future expectations of farmland value. In the author's opinion, this is too strong of an assumption to make, and therefore I conduct a distributed lag model that includes lags (past) and leads (future) of weather. Ample research has been done in agricultural economics to show that corn yields are only

[28]Figure A11 displays the mean climate for the study's early and late periods for the alternative climate variables of Degree Days $8 - 32°C$ and Degree Days $> 32°$C.

Table 6.4: Baseline Regression Results Across Two Time Periods

	Time Period	
	Early	Late
Degree Days $10 - 30°C$	-27.49	-26.45
	[35.88]	[36.51]
Degree Days > 30°C	-28.35	-29.79
	[88.90]	[90.85]
Precipitation	-20.88	34.40
	[33.87]	[45.19]
Precipitation^2	0.06	-0.09
	[0.13]	[0.12]
Wald Test of Joint Significance (p-value)	0.794	0.794
Number of Weather Variables Individually Different at p=0.05	0	0
Observations	30,702	30,702
R^2	0.0076	0.0076

Notes: The above table corresponds to the baseline model when divided two equal subsets of time. The panel labelled Early is for the panel of data from 1950-1978, while the right-hand panel, labelled Late epresents census years 1982-2012. In brackets are standard errors which have been clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

impacted by current weather realizations, are not affected by future or past weather events (Hsiang, 2016).

In Figure 6.2, the left-hand panel highlights the relationship of interest between farmland values and harmful degree days. I find that neither contemporaneous, future, or past harmful degree days are indistinguishably different from zero.[29] In contrast, the right-hand panel illustrates that only contemporaneous harmful degree days affects the variance in corn yields. This is a solid falsification test, and reassures us that the weather variables being used are of good quality. Table 6.5 shows the evolution of the baseline model's weather variables over different lags and leads.

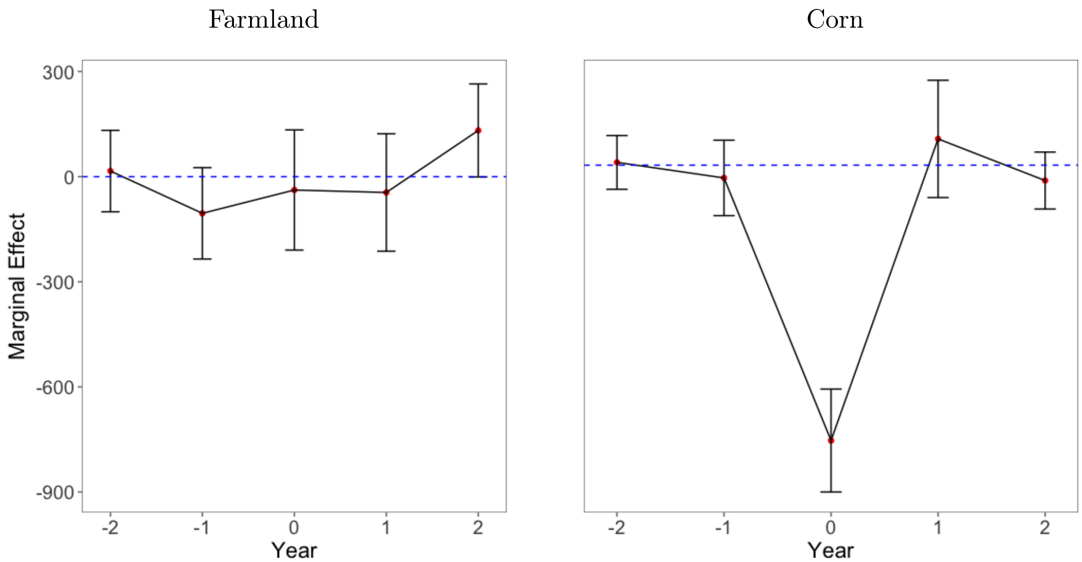
To identify if these weather shocks have a permanent or transitory effect on farmland values, I conduct an F-Test that the cumulative effect of each weather variable's lagged terms are jointly equal to zero. With an F-stat of 0.5543 and a corresponding p-value of 0.6959, I fail to reject the null hypothesis that these weather shocks have a temporary effect on the farmland market, and confirm that it is not a permanent one.

[29]Similar figures for the other primary climate variables, are found in the appendix as Figures A12 and A13 for the farmland and corn samples, respectively.

Table 6.5: Baseline Regression Results Across Two Time Periods

	Year				
	-2	-1	0	1	2
Degree Days $10-30°C$	-24.73	-24.72	-25.92	-25.67	-24.37
	[35.88]	[35.65]	[37.28]	[30.31]	[27.65]
Degree Days $> 30°$C	-5.11	-1.60	-20.86	-20.89	-53.56
	[101.76]	[101.99]	[94.10]	[83.13]	[80.54]
Precipitation	9.23	9.35	8.22	8.06	8.72
	[22.57]	[24.03]	[25.92]	[25.55]	[24.37]
Precipitation^2	-0.03	-0.03	-0.03	-0.03	-0.03
	[0.07]	[0.07]	[0.08]	[0.07]	[0.10]
Degree Days $10-30°C$ lag1	-3.78	4.64			
	[28.66]	[21.49]			
Degree Days $10-30°C$ lag2	22.48				
	[24.44]				
Degree Days $> 30°$C lag1	-81.03	-83.16			
	[76.11]	[77.83]			
Degree Days $> 30°$C lag2	-14.65				
	[54.23]				
Precipitation lag1	-33.43	-35.07			
	[24.09]	[23.73]			
Precipitation lag2	-16.62				
	[27.69]				
Precipitation^2 lag1	0.03	0.03			
	[0.06]	[0.06]			
Precipitation^2 lag2	0.03				
	[0.08]				
Degree Days $10-30°C$ lead1				0.51	-19.47
				[19.68]	[26.62]
Degree Days $> 30°$C lead1				5.10	-50.22
				[80.67]	[]
Precipitation lead1				5.47	-3.09
				[25.48]	[22.00]
Precipitation^2 lead1				-0.01	0.01
				[0.07]	[0.14]
Degree Days $10-30°C$ lead2					43.81*
					[25.49]
Degree Days $> 30°$C lead2					130.96*
					[73.44]
Precipitation lead2					-5.03
					[18.54]
Precipitation^2 lead2					0.09
					[0.08]
Observations	30,701	30,701	30,702	30,701	30,701
R^2	0.0213	0.0165	0.0034	0.0038	0.0239

Notes: The above table corresponds to regression results for farmland value from 1950-2012 with different lag(past) and leads(future) of weather variables.The left-most column, with a lag of -2, stands for weather two years prior the agricultural census. Whereas the column with lag 0 represents contemporaneous weather. Note that the right-most column has a lag of 2, indicating weather two years after each census. Standard errors are reported below coefficients, in brackets, and are clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.



Notes: These figures correspond to the marginal effects of harmful degree days, Degree Days 30°C for farmland value (left) and corn yields (right). While only contemporaneous harmful degree days explains variations in corn yields, we cannot detect any explanatory power for periods of harmful degree days in terms of explaining variation in farmland value. To interpret these standard errors, the readers should divide the value by 100,000.

Figure 6.2: Marginal Effects of Lags and Leads For Two Dependent Variables

Robustness Checks

The findings thus far have all been based on the usage of one set of temperature variables - Degree Days $10-30°C$ and Degree Days > 30°C - and one growing season, April to September. As a final series of robustness checks, I test the sensitivity of my findings by: 1)Using an alternative set of temperature variables, Degree Days$8-32°C$ and Degree Days >32°C , but do not change the growing season and 2) Using an alternative start and end of the growing season of March to August, with Degree Days$10 - 30°C$ and Degree Days > 30°C.[30]

Figure A16 uphold the finding that recent weather shocks cannot be distinguished from zero across time or through the inclusion of future and past weather terms holds for both the alternative season and degree day specifications. The inability to distinguish any of the four weather variables from zero in our baseline model is stable when the sample is split into sub groupings of study years for alternative growing seasons and weather variables. That we find less stability across space across these alternatives, is not that surprising and exemplifies that spatial heterogeneity is a very potent presence in farmland value and weather observations. Results from the placebo test conducted in the distributed lag model confirms that recent weather shocks have had a transient impact on changes in farmland values, as opposed to a

[30]The correlation coefficient between the Degree Days$10 - 30°C$ and Degree Days$8 - 32°C$ is 0.981, while the correlation coefficient between harmful degree day alternatives of Degree Days > 30°C and Degree Days > 32°C is 0.978, confirming that interchanging the pair of degree day terms will pick up the same signal in changes of farmland value. Similarly, when we change the seasons, the correlation coefficient for Degree Days > 30°C between the two seasons is 0.962, while the correlation coefficient for Degree Days $10 - 30$°C is 0.996. The correlation coefficient for growing season precipitation is 0.913.

permanent one.[31]

[31]See Figure A14 for the marginal effects of HDD 30 across cardinal regions.

CHAPTER 7

CONCLUSION

With the growing likelihood that accumulating greenhouse gases will change the impact climate, there has been growing interest in also measuring the impact of climate change on agriculture. Currently, agriculture is arguably one of the most researched sectors in the climate change impacts literature. In this thesis I combine elements of the Ricardian approach and panel approach to analyze the effects of weather shocks on the farmland market. Moreover, because these yearly fluctuations in weather are essentially random and independent of other unobserved determinants of agricultural outcomes, these panel estimates correct for omitted variable bias.

The overarching goal of this paper has been to conceptualize, explore, and calculate if recent weather shocks have been capitalized by farmers, in the form of changes in farmland value. This was accomplished in three stages. Specifically, I examined if the impacts of of weathers shocks on farmland value is stable across time and space sub groupings. I also divided the sample into regions that are identified as having more and less stable climates, and examined if the farmer with a less stable climate is more likely to capitalize an idiosyncratic weather shock. And lastly, I examine if farmers are forward looking or myopic through a distributed lag model.

This body of research is an extension of the increasingly popular method to frame farmers as forward thinking and not myopic. In contrast to focusing on survey data that represents an amalgam of public opinion and agricultural surveys, I restrict data observations to the stakeholder of interest, the farmers, and base identification upon how farmland values changes with weather realizations.

That I was unable to distinguishably conclude that any of my weather parameters were different from zero prompted a further exploration across regional and temporal subsets, upon which I conclude that while my findings are robust across time, they are notably sensitive when divided by geographical location. One alternative explanation to why we may not have found temporal differences in the effects of weather shocks is the fact that farmers within each state have adapted to climate change at different rates. So while it is likely that individually, states have different tolerances of weather shocks, across the two designated sub periods, it was relatively equal.

The decision to measure if weather shocks have the same effect on changes in farmland values, when farmers are split into regions of more and less climate stability, pairs nicely with our theoretical model. Such a division into more and less stable climates allows us to test the hypothesis that all else equal, the updating of a farmer's prior beliefs of the mean weather will be driven by the variability of weather (variance in weather realizations). However, caution should be taken when interpreting these results. Though I find stable results across alternative growing seasons and harmful degree day cut offs, that I do not acknowledge that these regions have uniquely different temperature thresholds is an important one. I cannot rule out that degree days are an overly restrictive functional form for this model. As such, future research would benefit by modeling the temperature effect on changes in land value in a more flexible form and utilize the entire distribution of weather, avoiding the issue of assigning temperatures as harmful and beneficial. The results of a preliminary cross validation exercise to identify the best specification and functional form to model the temperature nonlinearity are found in the appendix.These results are considerably more difficult to interpret, and deserve further scrutiny.

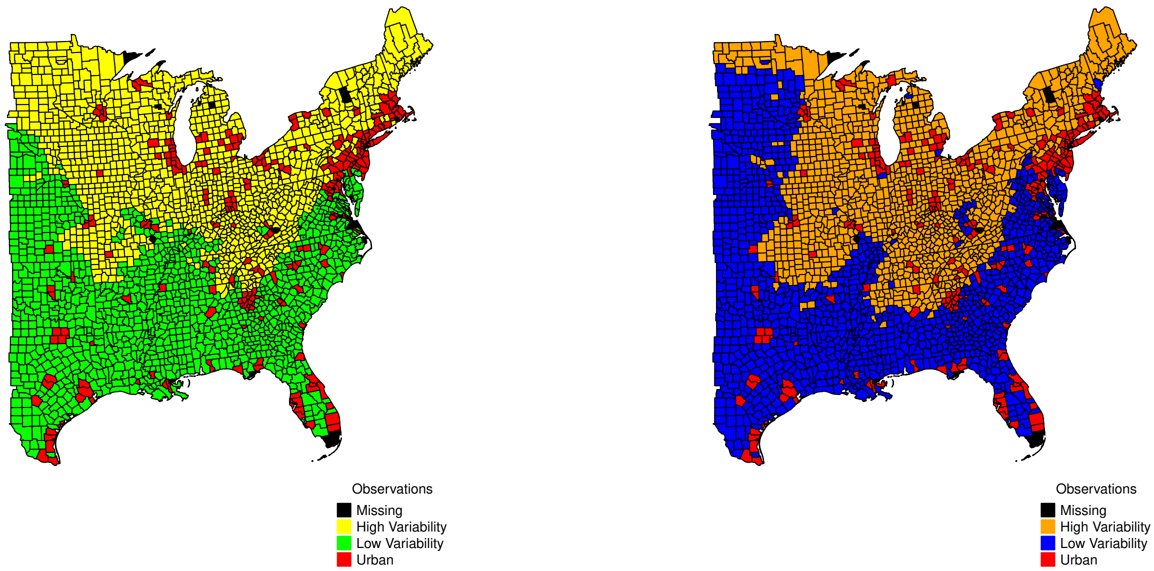
Perhaps the most promising piece of empirical results coming out of this study are the fact that I found convincing evidence that neither past, present, or future weather weather shocks are being capitalized by farmers in the farmland market. As a check, I find evidence supporting the intuition and previous research that corn yields are only impacted by current weather and not future or past weather, as is evidenced in Figure 6.2. Such a check helps reduce, though does not cancel out, the probability that the empirical results are spurious.

There are a number of important caveats which my analysis has not yet incorporated and warrant addressing. Firstly, the issue of utilizing fixed effects. A powerful advantage of time and location fixed effects includes the ability to capture all time-invariant and time-varying confounding factors, respectfully. However, by including both year and fixed effects, a large amount of variation is also captured and hence amplifies measurement error. As such, further research should explore the usage of alternative panel methods, such as the usage of a spatial lag model. A second caveat relates to the issue of government payments. As aforementioned in the Introduction, it is unclear if farmers undertake costly adaptation strategies to cope with a changing climate, when there is a history of the governmental agriculture support programs protecting farmers against substantial losses.

It is also of interest that lastly that changes in weather shocks do not actually cause changes in the farmland market. Figure 5.2 identifies that the greatest changes in farmland value over our sample period are not found in the most agriculturally productive areas (such as the Cornbelt), but the largest amount of appreciation has occurred in the Northeast corridor, and the southeastern US. This suggests the potential that spill overs from the housing market are actually behind changes in farmland market, rather than weather shocks.[32] To that extent, future research should investigate the usage of alternative dependent variables such as cash rent, which identify the expected return of agricultural production from a piece of land, and hence not be influenced by changes in land use expectations.

[32]It is true that the spill over from development pressure occurs on a different time scale than weather shocks, that is, the effect of development pressure is slower.

APPENDIX



Notes: This figure identifies the parent dataset when split into areas of high and low variability according to CV30 (left) and CV32 (right).

Figure A1: Division into Regions of High and Low Climate Variability According to CV30 and CV32

Table A1: Agricultural and Climate Variable Summary Statistics

Period	μ	min	max	σ
Sample	95.87	1.00	212.00	40.08
Early	69.50	1.00	171.2	26.32
Late	122.23	16.00	212.00	33.72

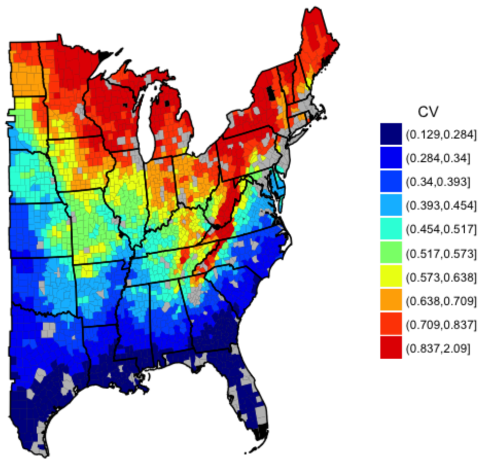
Values are county averages of a balanced corn yield panel, where N=631 and T=63, east of the 100$^{\text{th}}$ meridian. Counties were omitted if their population density was greater than 400 persons per square mile. The growing season is April through September. Corn yields are reported in bushels per acre.

Table A2: Agricultural and Climate Variable Summary Statistics for an Alternative Season

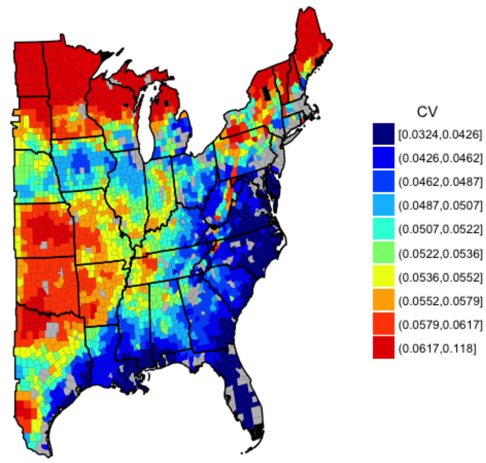
Variable	μ	min	max	σ
Farmland Value	1,755.35	50.39	21,807.05	1,325.92
Farmland Acres	240.38	0	217.6	181.5
Degree Days $8-32°C$	1,954.52	756.86	3,106.21	363.13
Degree Days $10-30°C$	1,470.93	563.98	2,203.97	247.37
Degree Days $> 30°C$	62.52	0	437.56	57.75
Degree Days $> 32°C$	28.27	0	282.38	34.45
Precipitation	580.67	140.01	1,474.5	156.05

Values are county averages of a balanced farmland panel, where N=2,193 and T=14, east of the 100$^{\text{th}}$ meridian. Counties were omitted if their population density was greater than 400 persons per square mile. The growing season is March through August. Farmland Value is reported in constant 2012 USD, Farmland Acres are in thousands of acres, and Precipitation is reported in millimeters.

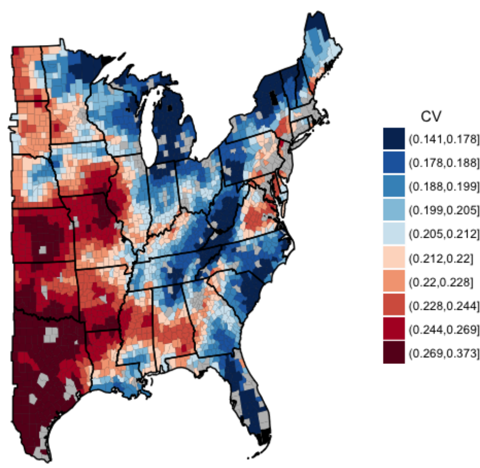
CV Degree Days $> 30°C$



CV Degree Days $10 - 30°C$

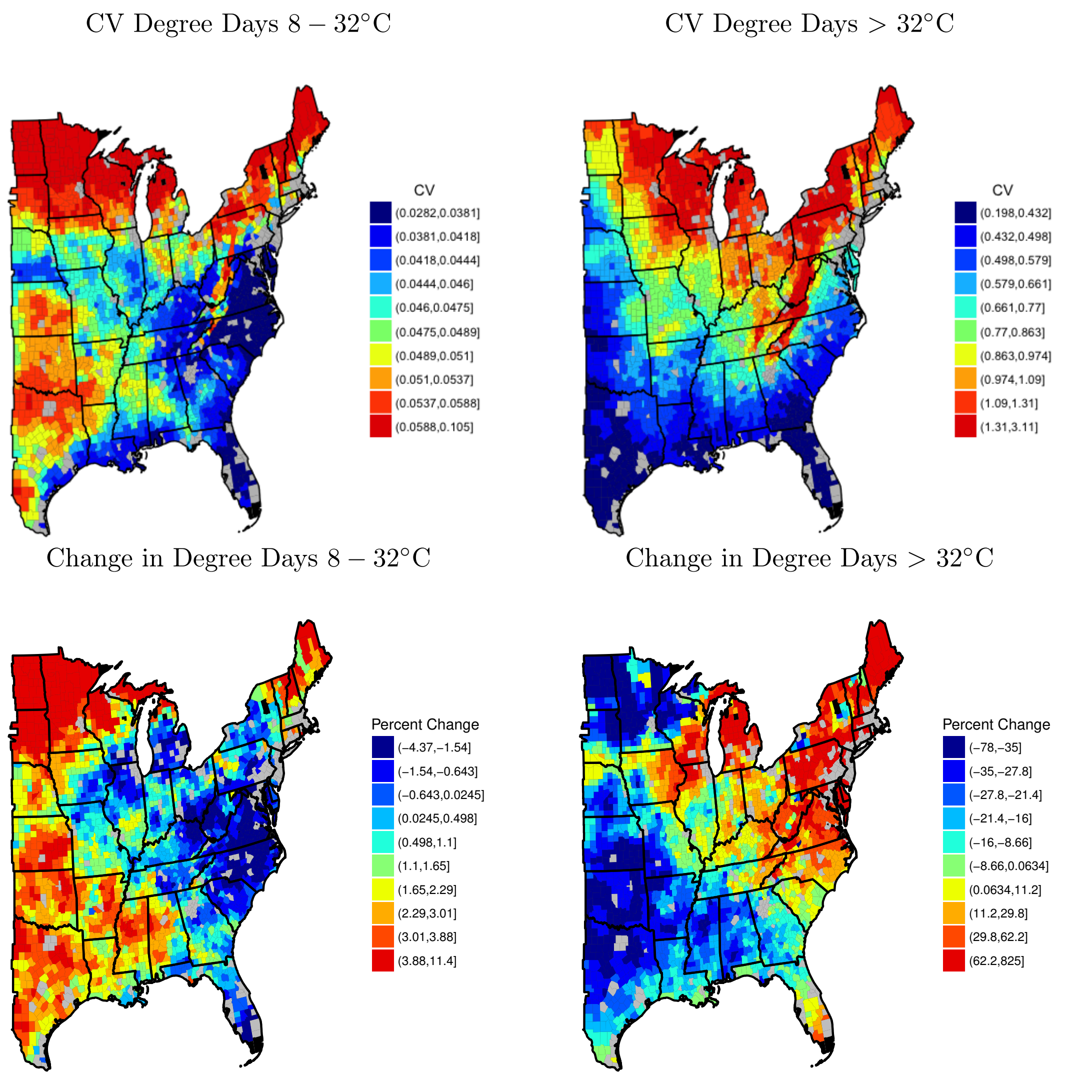


CV Precipitation



Notes: Scales are in Coefficient of Variation. Counties shaded in grey are urban, while counties shaded in black are missing.

Figure A2: Coefficients of Variation for Primary Climate Variables



Notes: The top panel shows the CV for alternative Degree Days, whereas the lower panel illustrates the percentage change in these alternative climate variables, between two periods (1950-1978) and (1982-2012). The growing season is April to September. Counties shaded in grey are urban. Counties shaded in black are missing.

Figure A3: CV and Percentage Change for Alternative Climate Variables

Table A3: Regional Averages of Farmland Real Estate and Climate Variables for CV32

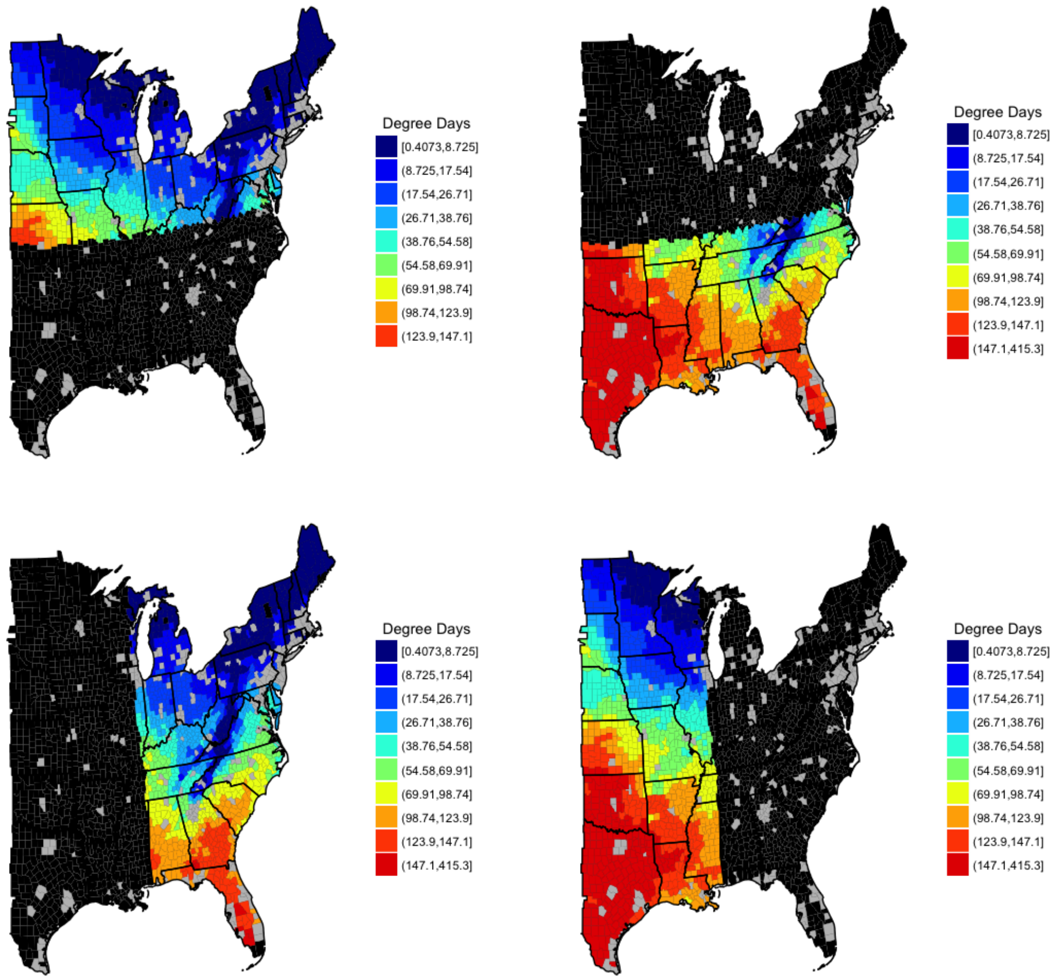
Variable	North	South	East	West	High	Low
Farmland Value	1,929.20	1,581.65	1,986.24	1,524.66	1,985.50	1,526.25
	[938.85]	[625.56]	[832.06]	[730.86]	[906.65]	[636.64]
Farmland Acres	265.54	215.25	146.16	334.52	214.94	265.80
	[178.66]	[172.44]	[89.85]	[192.57]	[136.79]	[207.12]
Precipitation	537.29	625.71	599.66	563.40	555.78	604.15
	[72.23]	[103.33]	[91.85]	[103.56]	[71.70]	[117.74]
Degree Days $8-32°C$	1,935.86	2,448.76	2,203.56	2,181.31	1,973.31	2,412.48
	[255.22]	[160.40]	[343.63]	[322.60]	[283.77]	[214.73]
Degree Days $10-30°C$	1,490.53	1,813.45	1,668.31	1,635.82	1,523.66	1,781.10
	[185.25]	[86.64]	[221.08]	[211.08]	[206.78]	[135.43]
Degree Days > 32°C	13.47	49.23	18.98	43.73	10.06	52.57
	[14.57]	[32.82]	[16.89]	[36.57]	[9.60]	[30.48]
Degree Days > 30°C	33.11	107.71	50.67	90.17	27.95	112.81
	[26.84]	[54.56]	[39.92]	[64.08]	[20.73]	[49.43]

Notes: Columns 2 through 4 correspond to geographic subdivisions of cardinal regions, as described in Chapter 4, each of which is N=15,351. The last two columns correspond to regions of high and low climate variability, when the sample is divided by the Coefficient of Variation for D.Days > 32°C. Standard deviations are in brackets. All dollar values are in constant 2012 USD. Farmland acres are reported in thousands of acres.

Table A4: Comparison of Conley Standard Errors and Clustered Standard Errors for the Baseline Model

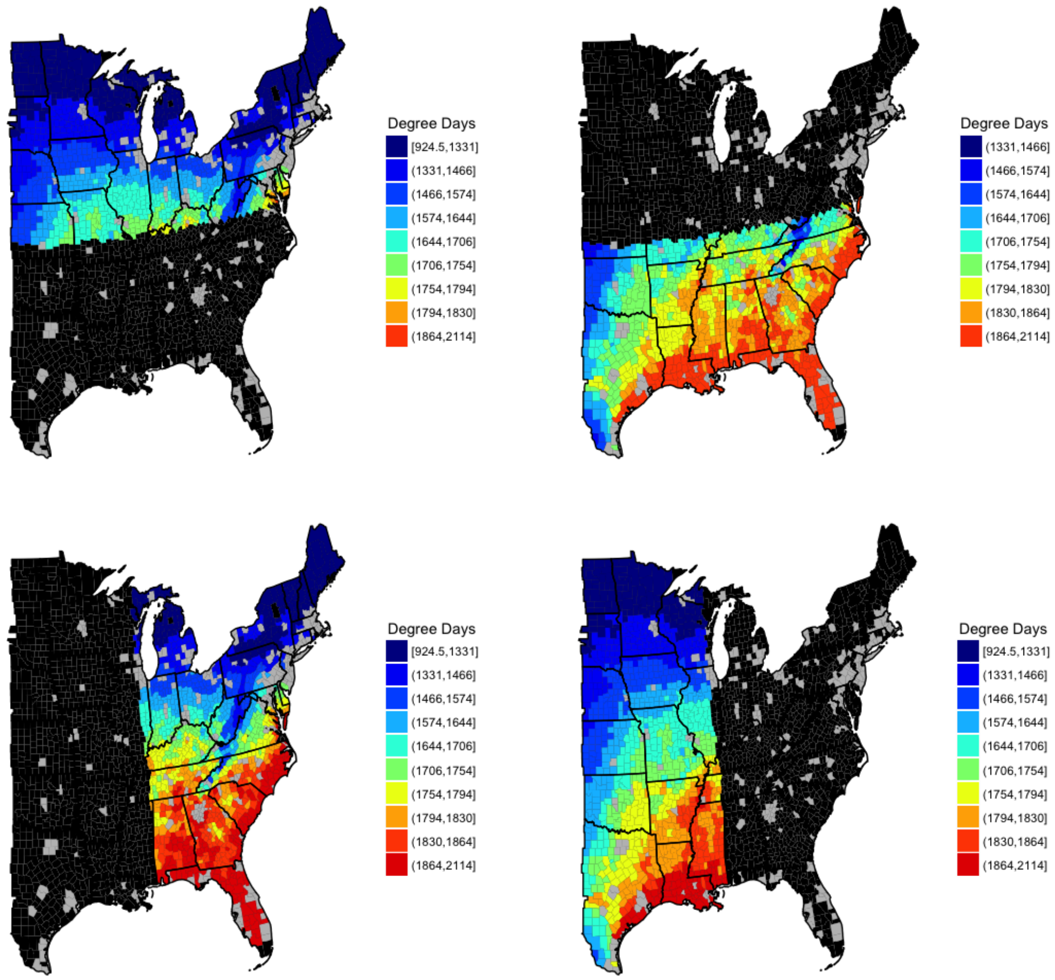
	Dependent variable:
	Log Farmland Value
Degree Days $10 - 30°C$	-25.92
	(3.28)
	[37.28]
Degree Days $> 30°$C	-20.86
	(10.28)
	[94.10]
Precipitation	8.22
	(4.96)
	[25.92]
Precipitation^2	-0.03
	(0.02)
	[0.08]
Observations	30,702
R^2	0.003417

Notes: This table corresponds to Table 6.1, albeit with Conley standard errors. Standard errors were treated with the semi-parametric routine of Conley (1999). A distance cut-off of 100 miles was used, along with bartlett kernels. Conley standard errors are in parenthesis, while standard errors clustered by state and year are in brackets. Notice that the clustered standard errors are at least 4 times as large as the Conley standard errors. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.



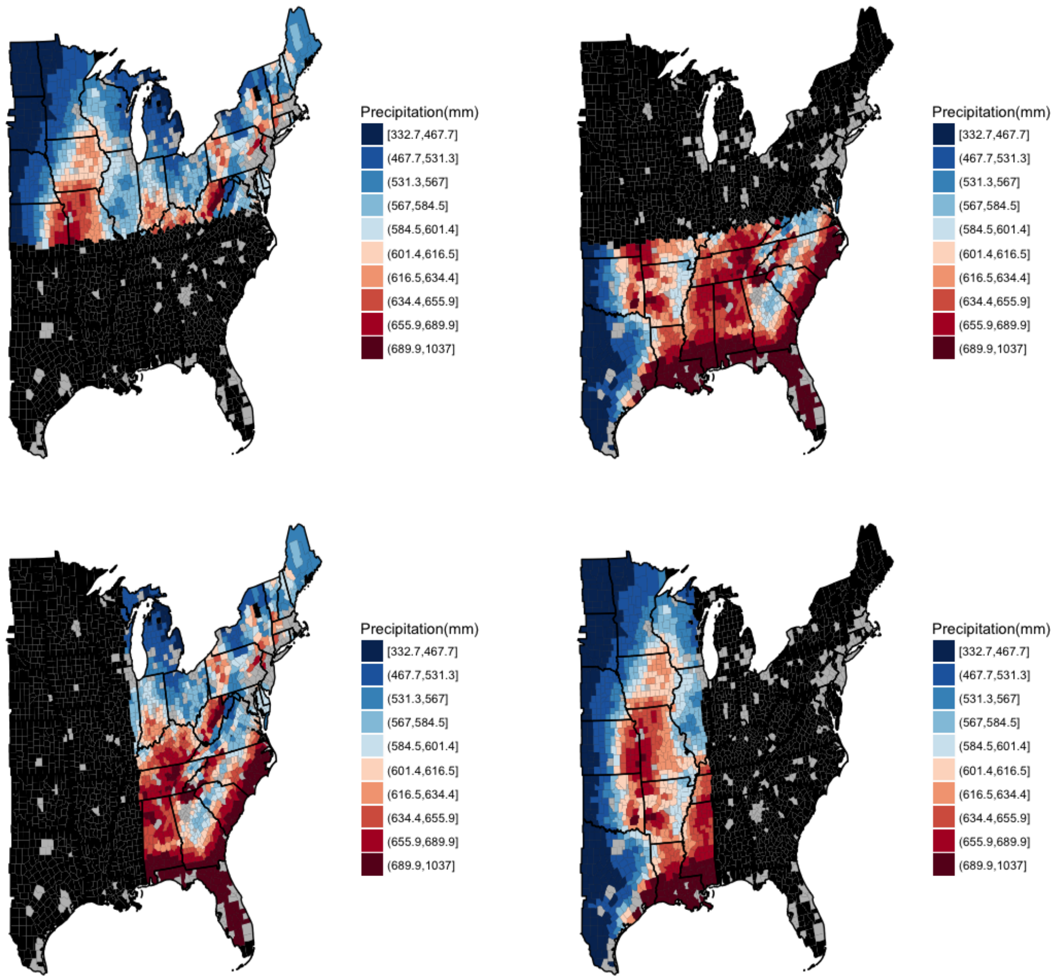
Notes: These figures correspond to harmful degree days, Degree Days $> 30°C$ for the growing season April - September, when our panel of farmland data is split into equally sized regions. For each region, $N = 549$ (North,South) and N=*548* (East,West) counties. Note that these are average exposures per year. Counties that are shaded in *grey* correspond to missing counties. Counties shade in *black* correspond to counties that are not in that particular region.

Figure A4: Degree Days $> 30°C$ Across Cardinal Regions



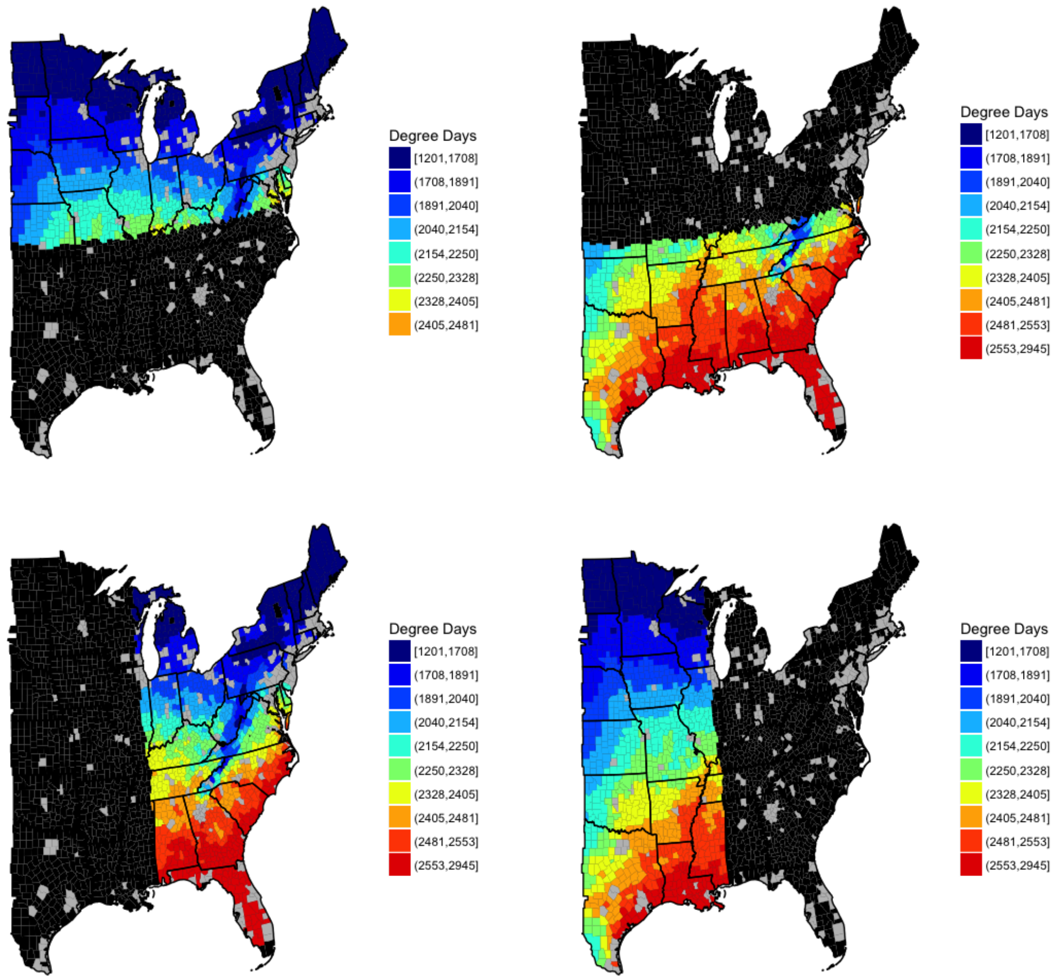
Notes: These figures correspond to normal degree days, Degree Days $10-30°C$, when the panel is split into cardinal directions. The season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties. Counties shaded in *black* correspond to counties that are not in that particular region.

Figure A5: Degree Days $10-30°C$ Across Cardinal Regions



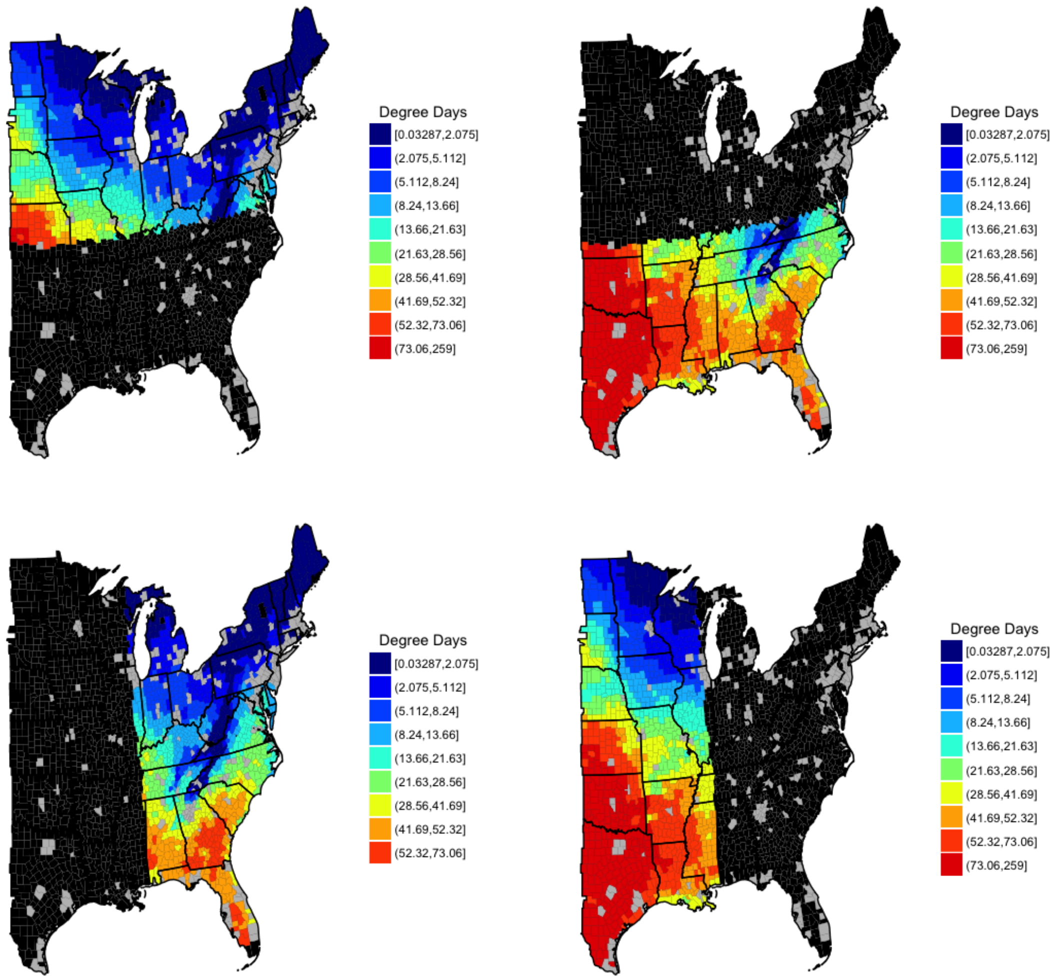
Notes: These figures correspond to precipitation averages, when the panel is split into cardinal directions. The season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties. Counties shaded in *black* correspond to counties that are not in that particular region.

Figure A6: Growing Season Precipitation Across Cardinal Regions



Notes: These figures correspond normal degree days, Degree Days $8 - 32°C$, when the panel is split into cardinal directions. The season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties. Counties shaded in *black* correspond to counties that are not in that particular region.

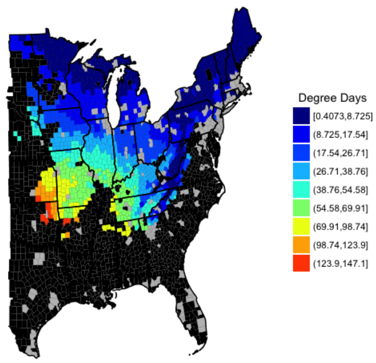
Figure A7: Degree Days $8 - 32°C$ Across Cardinal Regions



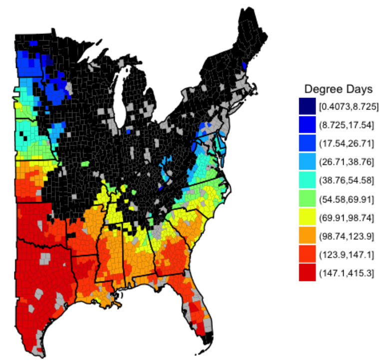
Notes: These figures correspond normal degree days, Degree Days $8-32°C$, when the panel is split into cardinal directions. The season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties. Counties shaded in *black* correspond to counties that are not in that particular region.

Figure A8: Degree Days > 32°C Across Cardinal Regions

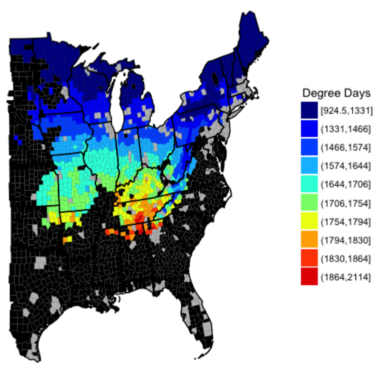
High Variability Degree Days 30°C



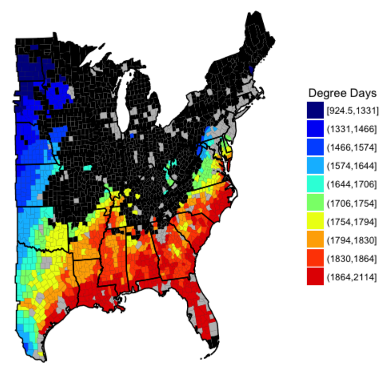
Low Variability Degree Days 30°C



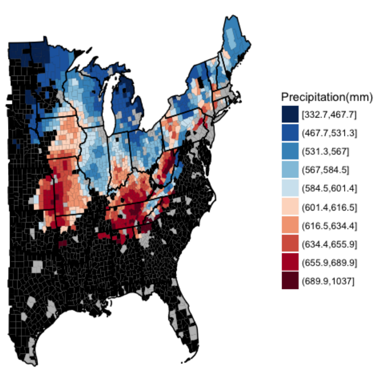
High Variability Degree Days$10-30°C$



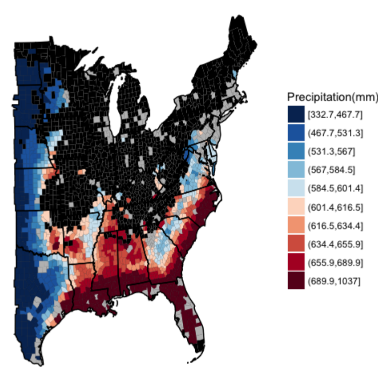
Low Variability Degree Days$10-30°C$



High Variability Precipitation



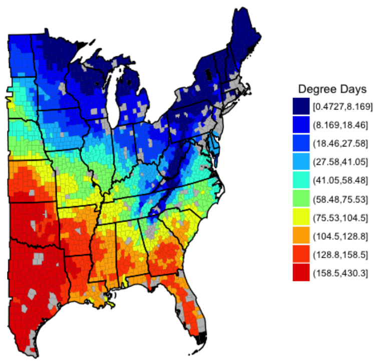
Low Variability Precipitation



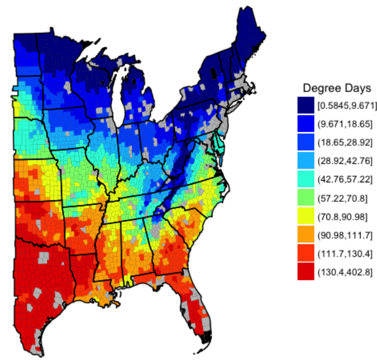
Notes: These figures correspond to the coefficient of variation for the three separate weather variables in our baseline model, for the April - September growing season. Regions shaded in red indicate a highly variable climate, whereas regions shaded in dark blue indicate the opposite. Counties that are *grey* identify missing or urban data.

Figure A9: Comparison of High and Low Climate Variability Weather Variables

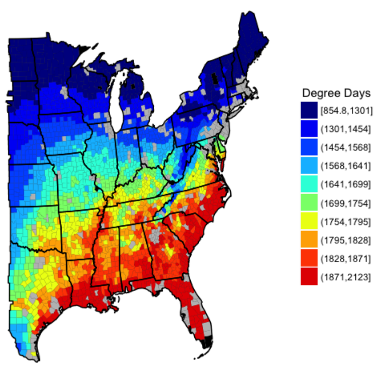
Early Degree Days $> 30°C$



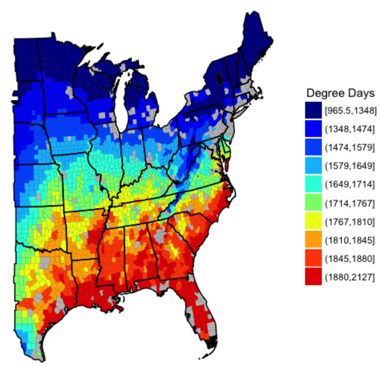
Late Degree Days $> 30°C$



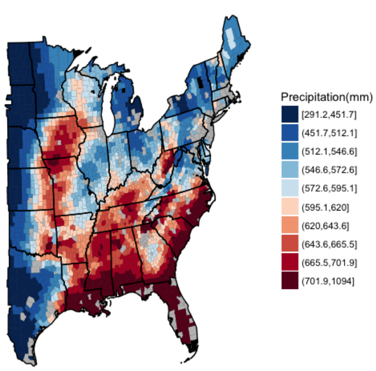
Early Degree Days $10 - 30°C$



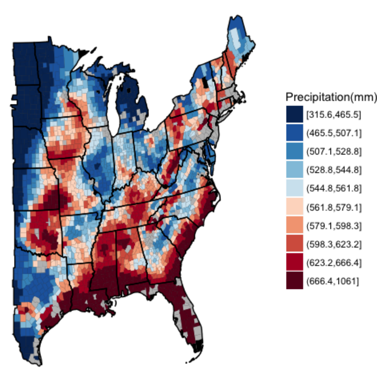
Late Degree Days $10 - 30°C$



Early Precipitation



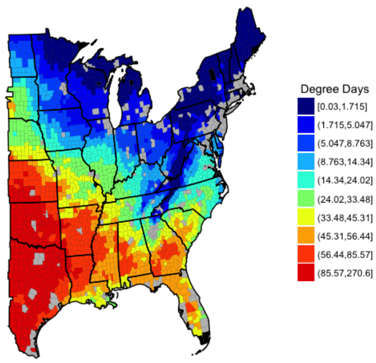
Late Precipitation



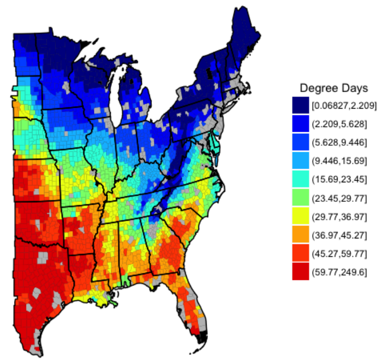
Notes: In the top panel, harmful degree days are compared across sub periods. In the lower panel, normal degree days are compared across sub periods. The early sub period is 1950-1978, while the late sub period is 1982-2012. The growing season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties.

Figure A10: Comparing Early and Late Climate Variables

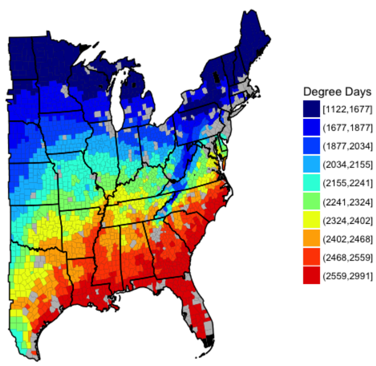
Early Degree Days $> 32°$C



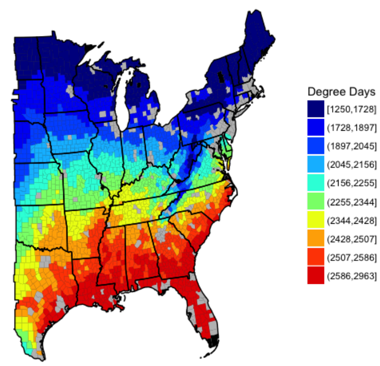
Late Degree Days $> 32°$C



Early Degree Days $8 - 32°C$

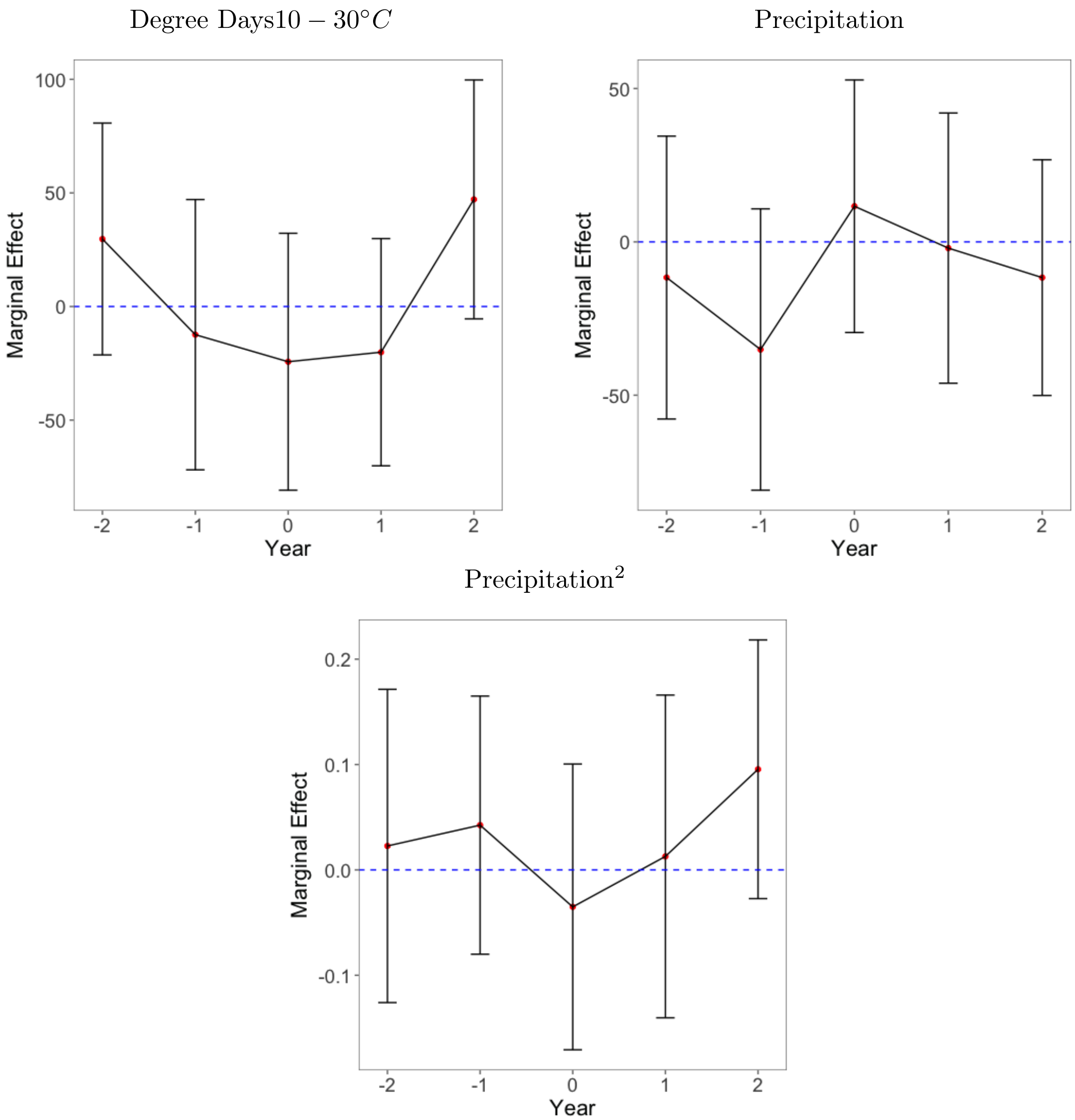


Late Degree Days $8 - 32°C$



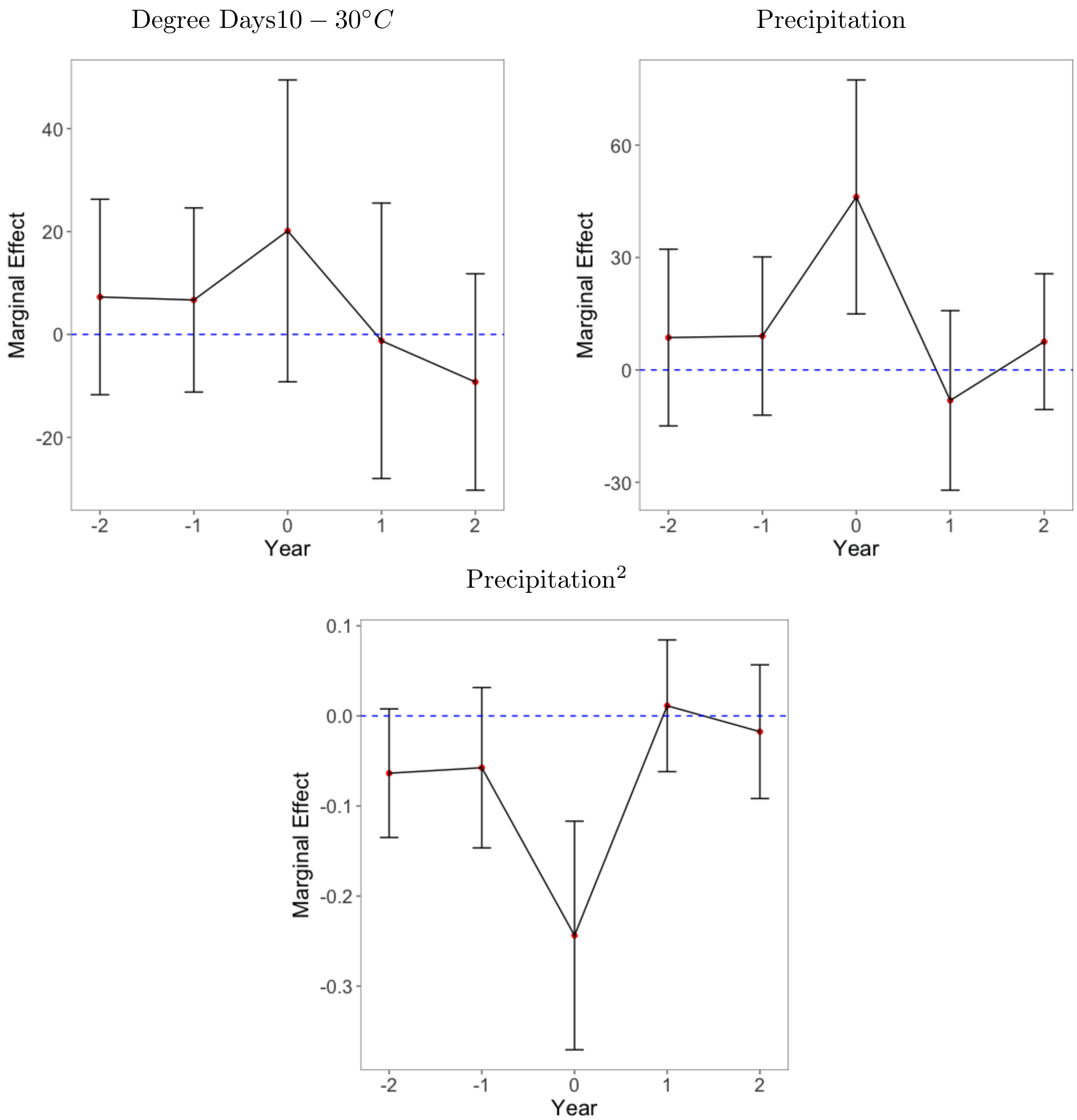
Notes: In the top panel, harmful degree days are compared across sub periods. In the lower panel, normal degree days are compared across sub periods. The early sub period is 1950-1978, while the late sub period is 1982-2012. The growing season is April - September. Counties that are shaded in *grey* correspond to missing or urban counties.

Figure A11: Comparing Early and Late Alternative Climate Variables



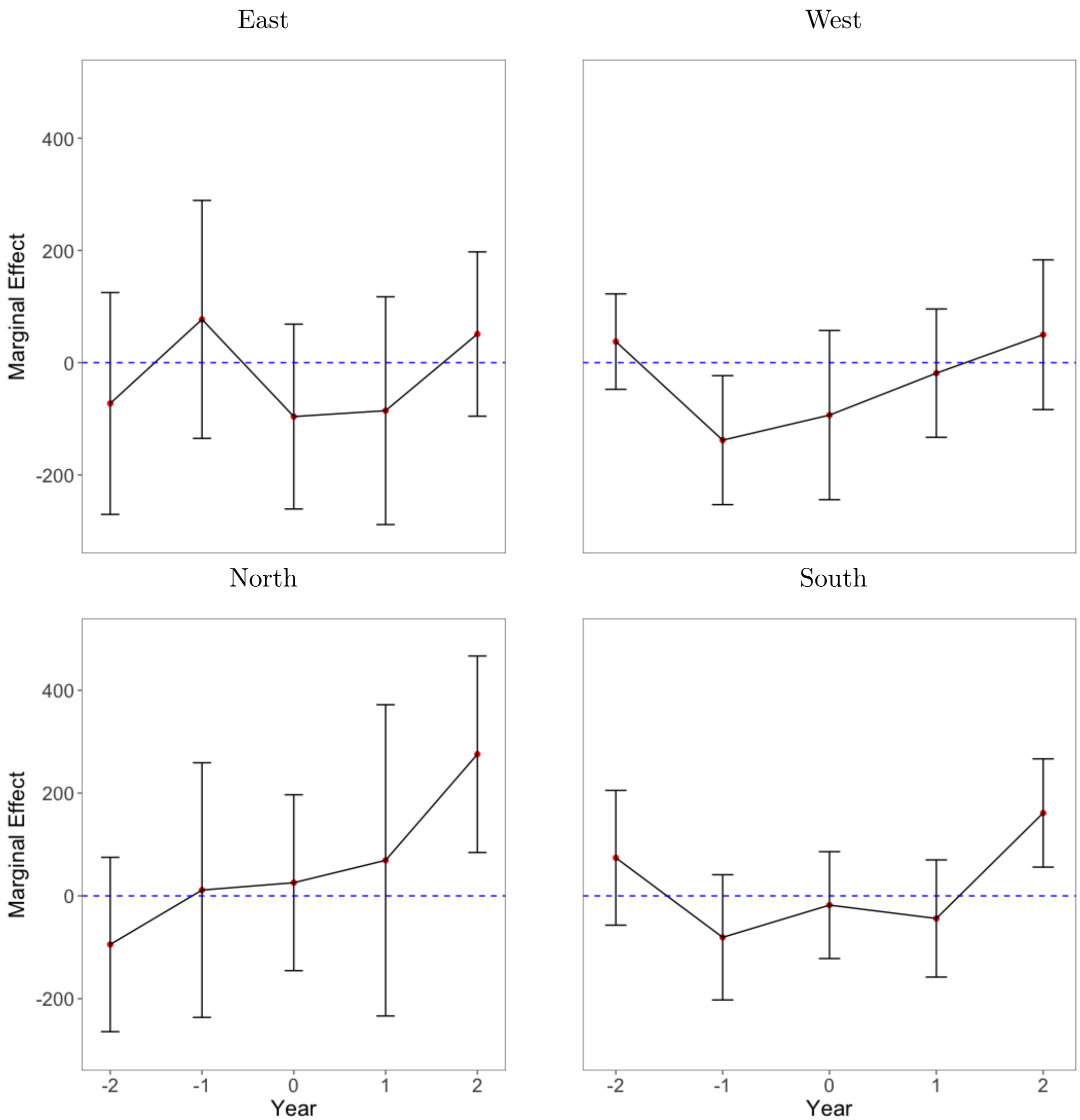
Notes: These figures correspond to the marginal effects of normal degree days and the two precipitation variables for farmland value during the Apr-Sept growing season. As was the case for harmful degree days, I cannot detect any explanatory power for periods of weather in terms of explaining variation in farmland value. To interpret standard errors, the reader should divide the entry of interest by 100,000.

Figure A12: Marginal Effects of Primary Climate Variables in Farmland Sample



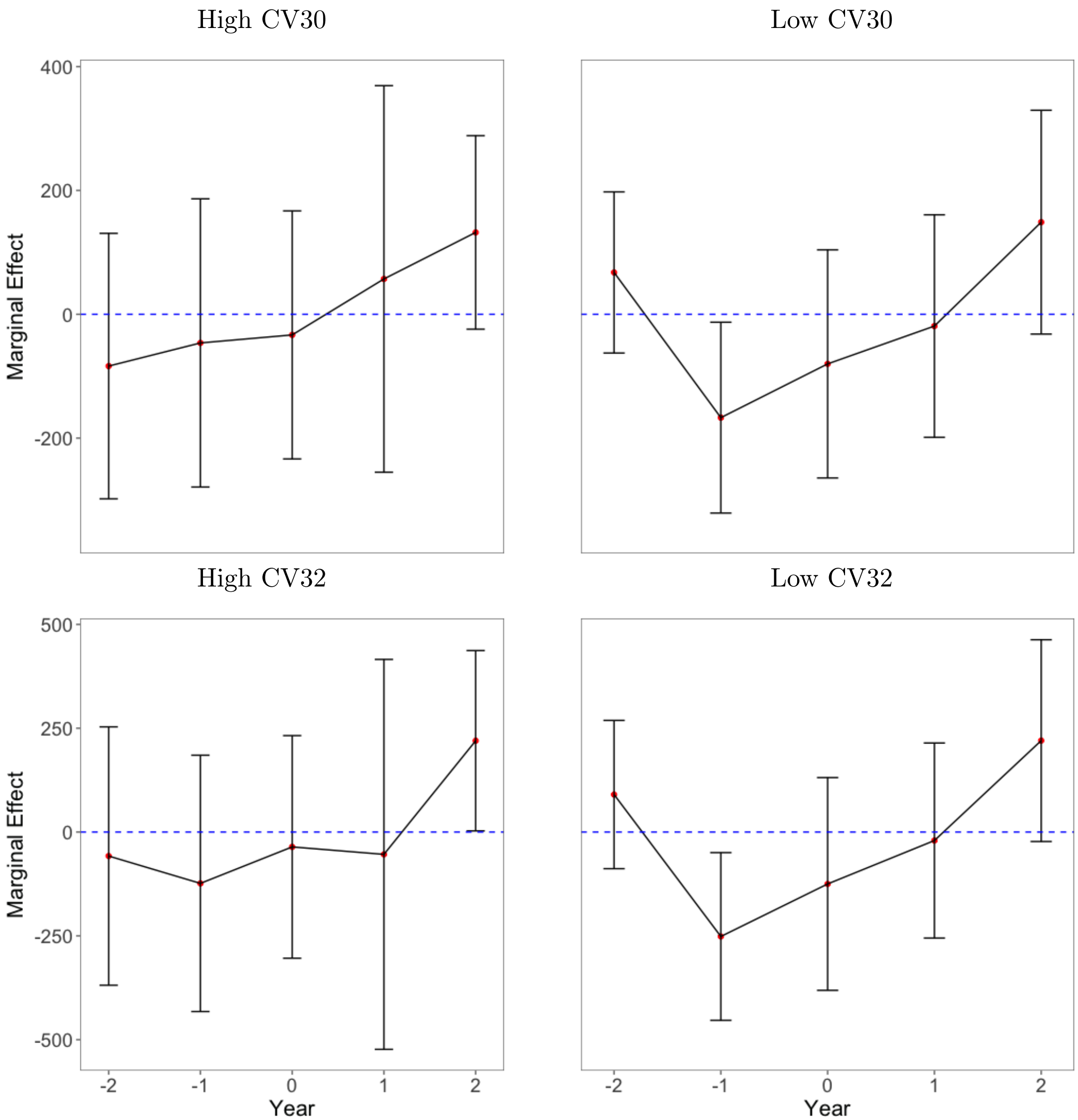
Notes: These figures correspond to the marginal effects of normal degree days and the two precipitation variables for corn yields for the April-September growing season.To interpret standard errors, the reader should divide the entry of interest by 100,000.

Figure A13: Marginal Effects of Primary Climate Variables in Corn Sample



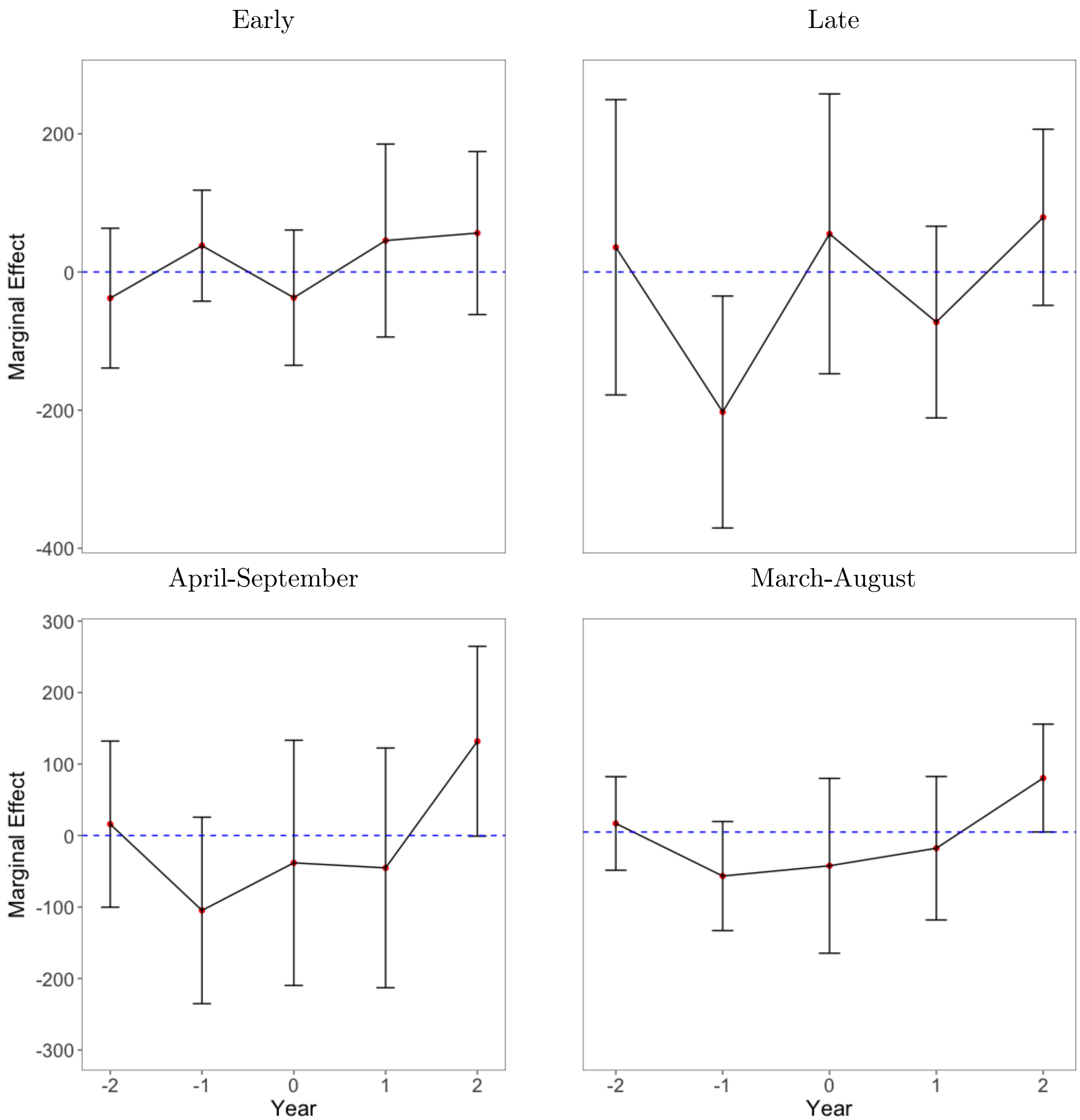
Notes: These figures reflect the cardinal regional disaggregate of Figure 6.2. To interpret standard errors, the reader should divide the entry of interest by 100,000.

Figure A14: Marginal Effects of Degree Days > $30°C$
Across Cardinal Regions



Notes: These figures reflect the marginal effects of different HDD in regions of high and low climate variability. The season is April to September. To interpret standard errors, the reader should divide the entry of interest by 100,000.

Figure A15: Marginal Effects of HDD 30 and HDD 32
Across Variable Climates



Notes: These figures reflect the marginal effects of HDD 30 across different periods (top) and seasons (bottom). Recall that the Early period is 1950-1978, while the Late period is 1982-2012. To interpret standard errors, the reader should divide the entry of interest by 100,000.

Figure A16: Marginal Effects of HDD 30 Across Seasons and Time Periods

Flexible Form

An area of interest for future research is to treat regional subdivisions with different temperature thresholds. Schlenker and Roberts (2009) illustrate that the threshold where temperatures become harmful to crop yields becomes slightly lower as one progresses from the south and advances northward in counties east of the 100$^{\text{th}}$ meridian. It is uncertain if this progression in temperature thresholds found between crop yields and temperatures, is similar to the relationship between farmland value and temperature. Hence, there is motivation to utilize the entire distribution of weather, so as to more closely disaggregate the effect of temperature on farmland value.

The flexible form specification model to implement is:

$$y_{it} = \int_{\underline{h}}^{\bar{h}} \phi_{it}(h)dh + p_{it} + p_{it}^2 + \alpha_i + \tau_t + \epsilon_{st} \tag{A.1}$$

where the LHS is equal to the natural log of farmland in county i and time period t, and with ϕ_{it} representing the cumulative distribution of heat (h) over the growing season. The upper and lower bounds $\underline{h}$ and $\bar{h}$ correspond to the range of temperatures experienced during the growing season. As in (4.1) , the terms p_{it} and p_{it}^2 represent precipitation and quadratic precipitation. County and time effects , α_i and τ_t absorb time invariant heterogeneity and technological change, respectively. The error term ϵ_{st} is corrected for spatial correlation with clustered standard errors by state and year. As opposed to degree days, the units of heat exposure used are total hours spent between sequential temperature bins.

The above integral can be approximated as follows:

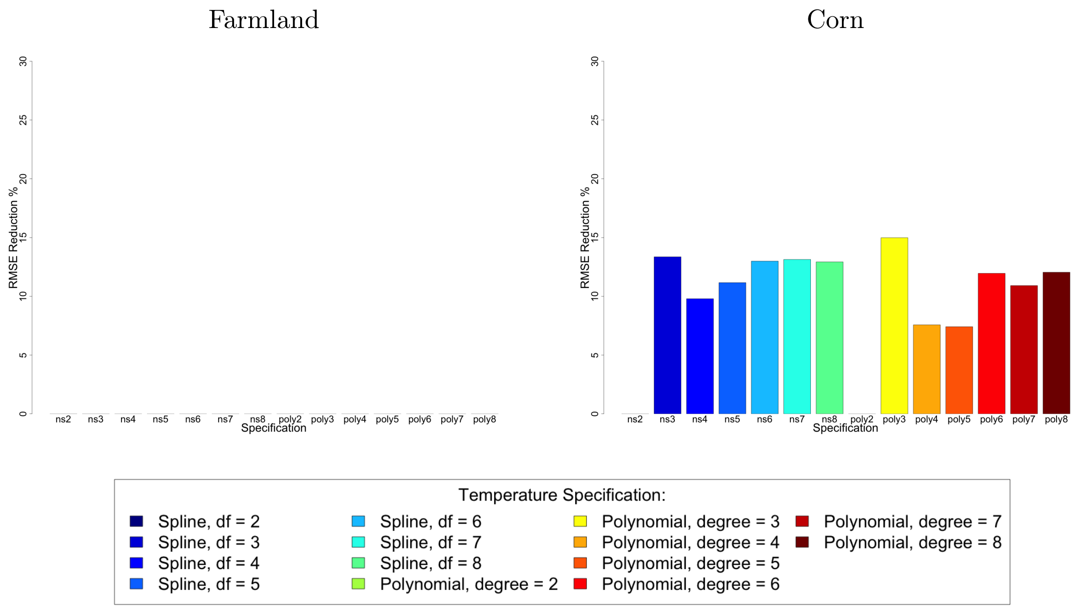
$$y_{it} = \alpha_i + \tau_t + \sum_{h=\underline{h}}^{\bar{h}} [\Phi_{it}(h+1) - \Phi_{it}(h)] + precip_{it} + precip_{it}^2 + \alpha_i + \tau_t + \epsilon_{st} \quad \text{(A.2)}$$

where Φ_{it} is the function for the cumulative distribution of heat [33]

Selection of functional form and specification are determined through a cross-validation out of sample exercise by using the out-of-sample root mean squared error (RMSE) statistic, where the model with the lowest RMSE is preferred. For a baseline, I consider a model consisting of year and county effects, but no weather variables. Upon calculation of said model, the percent reduction in the RMSE was calculated by including temperature and precipitation variables.

For the farmland sample, each model was randomly chosen with 13 out of the 14 sample census years. The remaining census year was then used to predict the farmland value. While it has been more common to use a k-fold of 5 or 10, because of the total number of years in my sample, I elect to utilize the leave-one-out cross-validation (LOOCV) technique. As a placebo test, the cross validation exercise was run with an alternative dependent variable of (log) corn yields. Figure A17 below

[33] As mentioned by Guiteras (2007), who utilizes a similar flexible functional form, a strong assumption that goes along with (1) is that the temperature bins are additively separable. In other words, I assume that the marginal effect of any bin is the same across time.



Notes: RMSE reductions for farmland value (left) and corn yield samples (right) are located above. It is evidence that while the model works for corn yields. The corn sample consists of N=631 and T = 50 (1954-2003), whereas the farmland sample consists of N=2,193 and T = 14 (1950-2012). Only contemporaneous weather was considered. RMSE Reductions are in percentages.

Figure A17: RMSE Reductions for Two Dependent Variables

provides the results of these RMSE reductions across numerous specifications.

Interestingly, this cross-validation exercise results for the farmland sample produced the greatest RMSE reduction polynomial and natural spline specifications of the 8th order, but are incredibly close to zero (0.003 percent improvement). In contrast, RMSE reductions for corn yields, when weather variables are included, range between 10 and 15 percent. It is likely that the year effect is not properly specified for our farmland model, hence the lack of improvement in RMSE. This ought to be the next step in research before we explore the more flexible marginal effects across regions.

BIBLIOGRAPHY

Adams, Richard M., "Global Climate Change and Agriculture: An Economic Perspective," *American Journal of Agricultural Economics,* 1989, 71(5), 1272-1279.

Adams, Richard M., Brian H. Hurd, Stephanie Lenhart, and Neil Leary, "Effects of Global Climate Change on Agriculture: An Interpretative Review," *Climate Research,* 1998, 11(1), 19-30.

Allison Edward H., Allison L. Perry, Marie-Caroline Badjeck, W.Neill Adger, Katrina Brown, Declan Conway, Ashley S. Halls, Graham M. Pilling, John D. Reynolds, Neil L. Andrew, and Nicholas K. Dulvy,"Vulnerability of National Economies to The Impacts of Climate Change on Fisheries," *Fish and Fisheries,* 2009, 10(2), 173-196.

Annan, Francis and Wolfram Schlenker, "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat," *American Economic Review,* 2015, 105(5), 262-266.

Anselin,Luc (1988). *Spatial Econometrics: Methods and Models.* Boston: Kluwer.

Arbuckle Jr., J. Gordon, Lois Wright, and Jon Hobbs, "Farmer Beliefs And Concerns About Climate Change and Attitudes Toward Adaptation and Mitigation: Evidence from Iowa," *Climatic Change,* 2013, 118(3-4), 551-563.

Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel, "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change," *Review of Environmental Economics and Policy,* 2013, 7(2), 181-198.

Burke, Marshall, John Dykema, David Lobell, Edward Miguel, Shanker Satyanath, "Incorporating Climate Uncertainty into Estimates of Climate Change Impacts, with Applications to U.S. and African Agriculture," Working Paper 17092, National Bureau of Economic Research, 2011.

Burke,Marshall and Kyle Emerick,"Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, 2016, 8(3),106-140.

Cabrera,Victor E., David Letson, and Guillermo Podesta, "The Value of Climate Information when Farm Programs Matter," *Agricultural Systems,* 2007, 93, 25-42.

Chay, Kenneth and Michael Greenstone, "Does Air Quality Matter? Evidence from the Housing Market," *Journal of Political Economy,* 2005, 113(2), 376-424.

Conley, T.G., "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics,* 1999, 92(1), 1-45.

Cyert,R.M. and M.H. DeGroot, "Rational Expectations And Bayesian Analysis," *Journal of Political Economy,* 1974, 82, 521-536.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "What do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature,* 2014, 52(3), 740-798.

Deryugina, Tatyana, "How do People Update? The Effects of Local Weather Fluctuations on Beliefs about Global Warming," *Climatic Change,* 118(2), 397-416.

Deschênes, Olivier and Michael Greenstone, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review,* 2007, 97(1), 354-385.

Feichtinger,P., and K. Salhofer, "The Valuation of Agricultural Land and the Influence of Government Payments," Factor Working Paper 10, 2011.

Fisher,A., M. Hanemann, M. Roberts, and W. Schlenker, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: comment," *American Economic Review,* 2012, 102(7), 3749-3760.

Fox,Jonathan F., Price V. Fishback, and Paul W. Rhode, "The Effects of Weather Shocks on Crop Prices in Unfettered Markets: The United States Prior to the Farm Programs, 1895-1932." *The Economics of Climate Change: Adaptations Past and Present.* University of Chicago Press, 2011. 99-130.

Group, Oregon State University PRISM Climate,"http://prism.orego nstate.edu," January 2017.

Guieteras, Raymond J, "The Impact of Climate Change on Indian Agriculture,"mimeo, MIT, Department of Economics, 2007.

Haines, Michael, Price Fishback, and Paul Rhode, United States Agricultural Data, 1840-2012. ICPSR35206-v3. Ann Arbor,MI: Inter-University Consortium for Political and Social Research, 2016-06-29.

Hatfield, J. G. Takle , R.Grotjahn, P.Holden, R.C. Izaurralde, T.Mader, E. Marshall, and D.Liverman, 2014: Chapter 6: Agriculture. *Climate Change Impacts in the United States: The Third National Climate Asessment,* J.M. Melillo, Terese (T.C.) Richmond, and G.W. Yohe, Eds., U.S. Global Change Research Program, 150-174.

Hirshleifer, Jack, and John G. Riley, *The Analytics of Uncertainty and Information.* Cambridge University Press, 1992.

Hobbs, J.E., "Measuring the Importance of Transaction Costs in Cattle Marketing," *American Journal of Agricultural Economics,* 1997, 79(4), 1083-1095.

Howden, S.Mark, Jean-Francois Soussana, Franceso N. Tubiello, Netra Chhetri, Michael Dunlop, and Holder Meinke, "Adapting Agriculture to Climate Change," *Proceedings of the National Academy of Sciences*, 104(50), 19691-19696.

Hsiang, Solomon M., "Climate Econometrics," Working Paper 22281, National Bureau of Economic Research, 2016.

Kaiser, Harry M., Susan J. Riha, Daniel S. Wilks, David G. Rossiter, and Radha Sampath, "A Farm-Level Analysis of Economic and Agronomic Impacts of Gradual Climate Warming," *American Journal of Agricultural Economics,*1993, 75(2), 387-393.

Kandlikar, Milind, and James Risbey, "Agricultural Adaptation of Climate Change: If Adaptation is the Answer, What is the Question?," *Climatic Change,* 2000, 45, 529-539.

Karl, Thomas R., Jerry M. Meililllo, and Thomas C. Peterson,(editors). *Global Climate Change Impacts in the United States.* Cambridge University Press, New York. (2009).

Kelly, David L., and Charles D. Kolstad, "Bayesian Learning, Growth, and Pollution," *Journal of Economic Dynamics and Control,* 1999, 23, 491-518.

Kelly, David L., Charles D. Kolstad, and Glenn T. Mitchell, "Adjustment Costs from Environmental Change," *Journal of Environmental Economics and Management,* 2005, 50(3), 468-495.

Lewandrowski, J.K., and R.J. Brazee, "Farm Programs and Climate Change," *Climatic Change*, 1993, 23(1), 1-20.

Lybbert,Travis J., Christopher B. Barrett, John G. McPeak, and Winni Luseno, "Bayesian Herders: Asymmetric Updating of Rainfall Beliefs in Response to External Forecasts," Paper 81, Economics Faculty Scholarship, 2004.

Malcolm,Scott, Elizabeth Marshall, Marcel Aillery, Paul Heisey, Michael Livingston, and Kelly Day-Rubenstein, *Agricultural Adaptation to A Changing Climate: Economic and Environmental Implications Vary by U.S. Region,* ERR-136. U.S. Department of Agriculture, Economic Research Service, July 2012.

Marzen, Chad G., and J.Grant Ballard, "Climate Change and Federal Crop Insurance," *Boston College Environmental Affairs Law Review*, 43 (2016): 387.

Meehl, G.A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, I.G. Watterson, A.J. Weaver and Z.-C. Zhao, 2007: Global Climate Projections. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw, "The Impact of Global Warming on Agriculture: A Ricaridan Analysis," *American Economic Review,* 1994, 84(4), 753-771.

Nickerson, Cynthia, Mitchell Morehart, Todd Kuethe, Jayson Beckham, Jennifer Ifft, and Ryan Williams, *Trends in U.S. Farmland Values and Ownership.* EIB-92. U.S. Dept. of Agriculture, Econ Res. Serv. Feb 2012.

Ortiz-Bobea, Ariel, "Is Weather Really Additive in Agricultural Production?," Discussion Paper 13-41, Resources for the Future, 2013.

Ortiz-Bobea, Ariel, "Climate Change Impacts on U.S. Agriculture: Accounting for Option Value of Farmland in the Ricardian Approach," *Unpublished Manuscript,* 2016.

Plantinga,Andrew J., Ruben N. Lubowski, and Robert N.Stavins, "The Effects of Potential Land Development on Agricultural Land Prices," *Journal of Urban Economics,* 2002, 52, 561-581.

Rejesus, Roderick M., Maria Mutuc-Hensley, Paul D. Mitchell, Keith H. Coble, and Thomas O. Knight, "U.S. Agricultural Producer Perceptions of Climate Change," *Journal of Agricultural and Applied Economics,* 2013, 45(4), 701-718.

Roberts,Michael J. and Wolfram Schlenker, "Is Agricultural Production Becoming More or Less Sensitive to Extreme Heat? Evidence from Corn and Soybean Yields," Working Paper 16308, National Bureau of Economics Research, 2011.

Schlenker, Wolfram and Michael J. Roberts, "Estimating the Impact of Climate Change on Crop Yields: The Importance of Nonlinear Temperature Effects," Working Paper 13799, National Bureau of Economic Research, 2006.

Schlenker, Wolfram and Michael J. Roberts, "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change," *Proceedings of the National Academy of Sciences,* 2009, 106(37), 15594-15598.

Schlenker,Wolfram, W. Michael Hanemann, and Anthony C. Fisher, "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach," *American Economic Review,* 2005, 95(1), 395-406.

Schlenker,Wolfram, W. Michael Hanemann, and Anthony Fisher, "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions," *Review of Economics and Statistics,* 2006, 88(1), 113-125. Accounting for Irrigation in the Hedonic Approach," *American Economic Review,* 2005, 95(1), 395-406.

Severen, Christopher, Christopher Costello, and Olivier Deschênes, "A Forward Looking Ricardian Approach: Do Land Markets Capitalize Climate Change Forecasts?," Working Paper 22413, National Bureau of Economic Research, 2016.

Shrader, Jeffrey, "Expectations and Adaptation to Environmental Risks," Working Paper, 2016.

Tol,R.S.J., S.Fankhauser and J.B. Smith, "The Scope For Adaptation To Climate Change: What Can We Learn From the Impact Literature?," *Global Environ.Change,* 1998, 8, 109-123.

United States Department of Agriculture, *US Department of Agriculture Climate Change Adapaptation Plan June 2014,* Web, 17 May 2017.

Weber, Elke U., "Experience-based and description-based perceptions of long-term risk: Why global warming does not scare us (yet)," *Climatic Change,* 77(1), 2006, 103-120.