Are U.S. Farmers Expecting Imminent Impacts from Climate Change? Evidence from Weather Shocks on the farmland market

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U.S. agriculture is likely to be affected by climate change due to its inherent reliance on climatic inputs. Previous research has mostly focused on measuring the potential impacts of climate change under varying assumptions of farmer adaptation. However, a lingering question is whether the market --the agricultural producers themselves-- have the impression that the climate is changing, and whether these changes are likely to be substantial. To answer this question, this paper develops a distributed lag panel model to explore the short-run effects of weather shocks on farmland values. Preliminary results suggest that weather shocks have permanent effects on the farmland market suggesting that farmers do perceive imminent substantial changes in climate.

Key words: climate change; agriculture; learning; farmland values
JEL Codes: Q12, Q51, Q54

The evidence regarding farmers' perception on climate is sparse and often problematic. There is some survey evidence showing that farmers do not tend to perceive the occurrence of extreme events and droughts as a result of climate change, but as the reflection of natural variability (Weber 2010, pg.335). Additionally, given the political context and the relatively polemical discourse surrounding climate change in the U.S., it seems that survey results based on farmer statements could be biased to reflect their political views (see Arbuckle et al. 2013; Rejesus et al. 2013). In fact, limited observational evidence exists on this matter. An example is Burke and Emerick (2015) who find US farmers have barely adapted to local climate trends based on long term changes in crop yields and climate (pg.4.)

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The goal of this paper is to determine whether US farmers expect imminent impacts from climate change as reflected by swings in the farmland market in response to weather shocks. Because climate is capitalized in farmland values, changes in a farmer's priors regarding his or her climate should therefore alter his or her farmland valuation. My analysis explores whether recent extreme events have a noticeable effect on farmer priors and therefore on farmland values and cash rents. Preliminary results suggest that recent extreme events, as measured by exposure to extreme temperature, seem to have only a temporary effect on the farmland market. This suggests that farmer do not perceive recent weather extremes as indicators of a changing climate.

The paper is organized as follows: Section 1 discusses the conceptual framework in greater detail and Section 2 describes the empirical strategy. Section 3 presents the data sources and summary statistics. I present the model results in Section 4 and conclude in Section 5.

1.Conceptual Framework

The basic idea in this paper is that farmland value reflects the discounted future stream of rents from the land and that this incorporates the local climate. If climate is expected to change, then the farmland market should respond accordingly in a permanent fashion. Farmers have priors about the climate they face, which comes from their experience in observing weather realization over time. The change in perception of local climate may arise from unusual realizations in weather. In other words, weather shocks may cause farmers to update their prior belief about the local climate.

The basis of my theoretical framework is a capitalization model and is found below in Equation 1:

Equation 1)

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

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, π represents profit, and *r* is the discount rate. *E* is the expectations operator and is conditioned on information available for farmer *i* at time *t.* Profit is defined as revenue minus costs plus government transfers, that is:

Equation 2) $\pi = py - wx + T$ [1,2]

where *y* is a vector of agricultural outputs, *p* a vector of output prices for said agricultural output, *x* a vector of input variables, w is a corresponding input price vector and *T* are government transfers.

Assuming that both government and output are functions of weather (z), we can rewrite y as $y = f(x, z)$. Therefore, Equation 1 can be rewritten to reflect weather, as found below in Equation 3:

Equation 3) $\pi = pf(x, z) - w\mathrm{x} + \mathrm{T(z)}$

[1] Eventually I will include government transfers. As of now, the agricultural census data (panel) includes a measure of total government payments received (average per farm). However, I strongly believe that this is an aggregate measure, and encompasses a host of aid programs, whereas I am specifically interested in isolating the effect that the FSA Disaster Assistance Program might have on the economic agent's updating behavior. An E-FOIA for said data has been submitted and I await the receipt of said dataset, which can be used as a robustness check.

[2] Ultimately, I will separate government rents from land rents, whereby I will distinguish economic rents by 1) returns from land (agriculture) and 2) returns from government transfers.

During the time period from now to the 2016 Annual AAEA Conference, I will be investigating how the expected land value per acre $E[y]$ maps to expected agricultural profits $E[\Pi]$ after a change in weather. To aid me along in this investigation, I utilize a Bayesian learning model. This is independent of the capitalization formula. Bayesian learning, with respect to climate change and its impact on agriculture, tells us that farmers are unable to instantaneously adjust to a change in climate because they do not perfectly observe this phenomenon. They realize it over time.[3] Let us first examine how farmers form their beliefs about weather in the next time period, as Equation 4 below:

Equation 4) $\mu_{i,t+1} = z_{it} + \mu_{it} + \varepsilon_t$

The LHS represents farmer i's expectation for weather in the upcoming time period (*t+1*). The variable z is a multidimensional variable of observed precipitation and temperature. The variable μ is a set of the farmer's previous expectations of weather, and is composed of unobservables. Lastly ε_t is white noise, whereby a farmer knows that prior expectations of what weather will be in the next time period, are not perfect. Thus the farmer forms his or her subjective assessment of what weather might be for the coming year based on currently available information and previously observed weather. The premise is a farmer *i* in time period *t* will update his or her belief with respect to how climate change impacts belief about future weather. I can rewrite Equation 4 as a Bayesian learning model (via a conditional posterior subjective probability equation)

[3] It is worth mentioning that economic agents can develop two types of adaptation: anticipatory versus reactive. The distinction between these two is of particular importance. Whereas reactive adaptation reflects individuals who are likely to respond to climate change after it occurs, anticipatory adaptation reflects deliberate decisions in which economic agents prepare for climate change (Fankhauser et al. 1999, pp.67-68.) Attempts to distinguish between those farmers that are anticipatory versus reactive will be incorporated into my econometric methodology in time for the conference.

as Equation 5:

Equation 5) $\pi_{e|f} = \lambda_e \pi_f + (1-\lambda) = \pi_e + \lambda_e(\pi_f - \pi_e)$

Equation 5 states that farmer i has an initial belief that the weather in the upcoming time period ($t+1$) will reflect their previous expectations with probability π_e. At the same time, they receive a competing subjective probability of π_f that can be thought of as forecasts for weather for the upcoming time period (t+1), from either local or national weather sources. λ_e represents the farmer's updating weights and represents his or her confidence in π_f and its source of information.[4] In the next section, I discuss my econometric strategy that transforms my theoretical model into an empirical model via a distributed lag model that has fixed-effects.

2.Econometric Strategy

My empirical method is based on panel data, which according to Burke & Emerick (2015) is preferred over a cross-sectional data set in large part because of omitted variable bias concerns. While I acknowledge that average ("long run" variations in) climate might very well be correlated with unobserved time-invariant factors, my "short run", annual variations in climate within a given area can be argued to be random, and therefore better identifies the effect of changes in climate variables on economic outcomes (pg.2.) It is of utmost importance to note that this panel remains unbalanced (n = 2826 counties.) Missing observations have been purged from the variables of interest,

[4] This learning model is similar to Lybbert et al(2004), with some modifications. It is a temporary idea that is being entertained as a learning model, with a firm belief that by the time of the conference, I will have constructed a different learning model that does not incorporate forecasts.

which leads me to conclude that there is an underlying "bug" in my model's code. This will be a primary focus of mine to correct for between now and the conference.

While (to my knowledge) my econometric approach cannot be linked to a single study to date, it is similar to Deschênes & Greenstone (2007), in that I too use a county-level panel data file that is constructed from USDA Agricultural Census, to examine the effect of weather on the value of land and buildings. However, whereas Deschênes & Greenstone (2007) examine the effect of weather on the value of agricultural profits conditional on county, and county by year fixed effects, I estimate the effect of weather on the estimated market value of land & buildings conditional on county, and county by year effects, through a finite distributed lag model in Equation 6 below:

Equation 6)

$$y_{it} = \alpha_i + \gamma_{it} + \sum_{n=0}^{N} \beta_n X'_{i,t\text{-}n} + u_{it}$$

where y_{it} represents the value of agricultural land per acre in county i for year t. The t subscript identifies that this mode can be estimated in any year for which data is available (Deschênes & Greenstone 2007, pg. 365). The $X'_{i,t\text{-}n}$ vector is a vector of observable weather determinants, all of which are time varying. Notice that there is a subscript for the X'_{it} vector that includes an n. This n represents the lag length (or lag period). The α_i term represents a full set of county fixed effects. What is appealing in including county fixed effects is its ability to absorb and remove all unobserved county-specific time invariant determinants of my independent variable. Such time invariant determinants include soil quality (Deschênes & Greenstone 2007, pg.367). The γ_{it} term represents county by year fixed effects. The last term in Equation Six is the error term, which is an idiosyncratic shock.

Heteroskedasticity, serial correlation, contemporaneous correlation, and spatial errors are four significant concerns when it comes to running panel linear models. As of the time of submitting this paper, I have not corrected for all of these issues. More specifically: while I did detect heteroskedasticity and serial correlation in my model (via the Breusch-Pagan Test Against Heteroskedasticity and Breusch-Godfrey Test for Serial Correlation, respectively), the predicaments of not correcting for spatial error and contemporaneous correlation still remains at large[5]. As a first step to correct for these two issues, I ran coefficient tests to calculate robust covariance matrix estimators (a la Arellano) and updated the standard errors.

The motivation to have a fixed effect model take the functional form of a finite distributed lag model was thus: I anticipate that assuming the farmer is Bayesian in learning, that the effect of weather (weather shock) on a farmer's updating behavior is not instantaneous, but is rather distributed over periods of time. Moreover, I believe that my model should be in tandem with economic theory in that after *n* lags, the effect of Degree Days on the dependent variable should extinguish.

As such, I can state that the current value of land and buildings in time *t* and county *i*, is a function of current and past weather events $X'_{it}, X'_{i,t-1}, \ldots X'_{i,t\text{-}n}$, where the last term $X'_{i,t\text{-}n}$ indicates that after *n* lags, the effect of previous weather events on current land and building values has been exhausted.

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[5] I am aware that the usage of Conley Standard Errors needs to be implemented to help correct for spatial errors, whereas for cross-sectional correlation, I must first test for uniformity and non-stationarity.

The parameter β_n is known as the distributed lag weight and it can be interpreted as measuring the effect of previously observed weather events $\Delta X'_{t\text{-}n}$, on the expected current value of land and buildings $\Delta E(y_{it})$, *ceteris paribus.* In other words, $\frac{\partial E(y_{it})}{\partial X'_{i,t\text{-}n}} = \beta_n$.

A note of clarification: it is often a concern that X'_{it} and $X'_{i,t-1}$, along with all other pairs of lags will have high collinearity, but I believe that weather fluctuations (my X'_{it}) are random in the *within* dimension of our panel data, and hence, I believe this mitigates this issue of collinearity. This belief is based on the idea that I have the correct number of lags. If this number is misspecified, then my lag distribution will be inaccurate and the cumulative impact of Degree Days on land values will be biased. We now turn to Data Sources and Summary Statistics.

3.Data Sources and Summary Statistics

Data Sources

Agricultural Production Data

My agricultural data comes from the USDA Agricultural Census, which is composed of county-level panel data and published every five years. Chay and Greenstone (2004) 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 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.

The included census years are 1987, 1992, 1997, and 2002.[6] The dependent variable I chose for my regression analysis is the market value of land and buildings per acre. I believe this to be an appropriate representation of the discounted benefits of net return to land rents.[7] Other variables that show up in my summary statistics, but which have not yet been incorporated into my regression analysis because of continuous difficulties with balancing my panel, include total average government payments received per farm, total cropland acres (average per farm), the market value of agricultural products sold (average per farm), and the farm production expenses (average per farm.)

It is important to mention that I've focused my analysis on counties in the United States that fall east of the 100th meridian. This is largely motivated by the fact that counties lying west of the 100th meridian typically rely on subsidized irrigation systems. The inclusion of these counties in my analysis could significantly bias my finding (Burke & Emerick 2015; Schlenker, Hanemann, and Fischer 2005.) Because of this, I intend to follow the methodology of Burke & Emerick (2015), Deschênes & Greenstone (2007), and Schlenker, Hanemann, and Fisher (2005), hereafter SHF 2005, and separate counties based on whether or not that county is defined as being irrigated or not. The criteria used to determine whether or not a county is irrigated or nonirrigated differs between Deschênes & Greenstone (2007) and SHF (2005.) Whereas the former use the criteria of 10% of that county's farm acres being irrigated (i.e. irrigated acres/ total farmland acres), the latter use the criteria of 20%.

[6] Like Deschênes & Greenstone (2007), I opted not to include the 1978 and 1982 agricultural census years in my analysis because of missing production expense information.
[7] This variable, and all other monetary variables used in this study have been converted to constant 2002 dollars.

Climate Data

The climate data used in this study comes from the weather data compiled by Schlenker & Roberts (2009). It consists of interpolated monthly mean, maximum, and minimum temperature and precipitation amounts for 4km grid cells across the entire US from 1946 to 2005**.** I restrict this dataset to match with my aforementioned study period and geographic region of interest. A strong nonlinear relation between plant growth and weather (temperature and precipitation)[8] has been proven to exist (Schlenker & Roberts 2009, pg.15594.) These nonlinearities are typically represented by using the concept of growing degree days – the amount of time a crop is exposed to temperatures between specific upper and lower bounds.

Every crop has a threshold (range) of temperatures between which it can absorb heat. The upper limit of this temperature range produces adverse impacts on not only the yield of that crop, but also that crop's health. Recall that one of my chief interests in this study is to examine how farmers will perceive changes in annual weather. I therefore define a *weather shock* [8] as any Degree Day observation that exceeds that upper limit. More specifically, I decide to use a temperature threshold of 30°C, based on the fact that my climate data stems from Schlenker & Roberts (2009), who construct their weather data from the growing criteria of cotton, soybeans, and corn. The thresholds of these crops are: 32°C , 30°C, and 29°C, respectively.[9] In total, then, I have two temperature variables: the first with a base of 10°C and ceiling of 30°C, the second with a base of

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[8] For the time being, weather shocks are only reflected with respect to degree days. By the time of the conference, they will also reflect precipitation shocks.

[9] A weather shock of degree days above 30°C is the minimal temperature threshold I can use for all three crops. It is true that such a variable will not capture the entire exposure of degree days above 30 °C for cotton (e.g. there will be degree days between 30°C and 32°C that do not adversely affect cotton). To more accurately reflect the exposure of cotton to corresponding adverse temperature threshold, I will incorporate a degree days above 32° for cotton by the time of the conference.

30°C. I will refine these temperature variables (and weather shocks) between now and the conference. Lastly, it is important to demarcate that I will follow the standard agronomic approach in modelling the growing season between April 1 through September 30.[10] In addition, the months of January, April, July and October are commonly used to demarcate seasonality. Depending on the crop and locality, a given crop has different growing cycle with respect to start and end dates. For my initial analysis, I do not include this seasonality effect but will incorporate it before the conference.

Summary Statistics

Table 1 reports county-level summary statistics from the Agricultural Production Data for my study period of 1987-2002, and individually reports the Agricultural Census findings for Agricultural Census years 1987,1992,1997, and 2002, respectively. This sample comprises a balanced panel of 2,826 counties. The variables falling under the Annual Financial Information category have all been converted to constant 2002 dollars. Over the course of my study period, the number of farms per county increased by approximately 3 %, while the average value of land & buildings (per acre) increased by nearly 39%. What is interesting, and will merit further investigation, are the changes across variables between 1987 and 1992. Notably, while the number of farms per county decreases roughly by 9%, the corresponding average value of land & buildings between 1987 and 1992 increases by approximately 1.3%.

Some words of caution when reviewing this table. Firstly: I am highly skeptical that the total government payments made is not highlighting what I am after, which are

[10] The same growing season is used in SHF 2005; Schlenker & Roberts 2009; Deschênes & Greenstone 2007; and Burke & Emerick 2015.

contributions from the FSA's (Farm Service Agency) Disaster Assistance Program which are meant to provide assistance to farmers in light of natural disasters such as flood and drought (i.e. consequences of weather shocks.) An E-FOIA has been submitted for this particular dataset, and if obtained in time for the conference, will serve as an interesting robustness check. Secondly: I have not yet separated counties based on whether or not they are *irrigated*, due to time constraint.

Table 1: County-Level Summary Statistics

	1987	1992	1997	2002
Farm characteristics				
Number of Farms	725	661	656	747
Land in farms(th.acres)	309	307	303	300
Total Cropland(th.acres)	155	149	148	152
Acres of Idle Farmland(th.acres)	13	8	7	13.
Annual Financial Information				
Avg.Value Of Land & Buildings ($1/acre)	1501	1521	1696	2085
Farm Revenues($mil)	73994	70807	75057	68242
Total Farm Expenses($mil)	58807	56918	57392	59055
Net Income($mil)	14742	13273	16223	13741
Total Government Payments($mil)	5393	2150	1687	

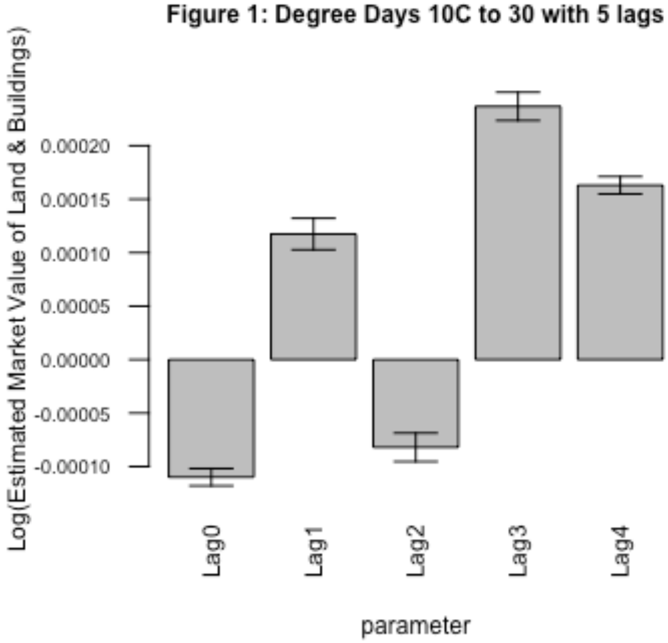
Notes: Averages are calculated for our balanced panel of 2,826 counties.

4.Results

This section presents the main empirical results of the paper. The preferred specification includes two temperature variables (degree days above 30°C and degree days between 10°C and 30°C) with five temporal lags. These lags were created from the Schlenker and Roberts (2009) weather dataset, in which there is annual weather data. To illustrate the year to which lags correspond, lag 0 corresponds to the current agricultural census year, and lag 4 corresponds to the year immediately after the previous agricultural census (e.g. if lag 0 equaled the 1987 census, lag 4 equaled 1983.) In addition to graphing these distributed lags, confidence intervals have been included and represent the “box and whiskers” element of each graph.

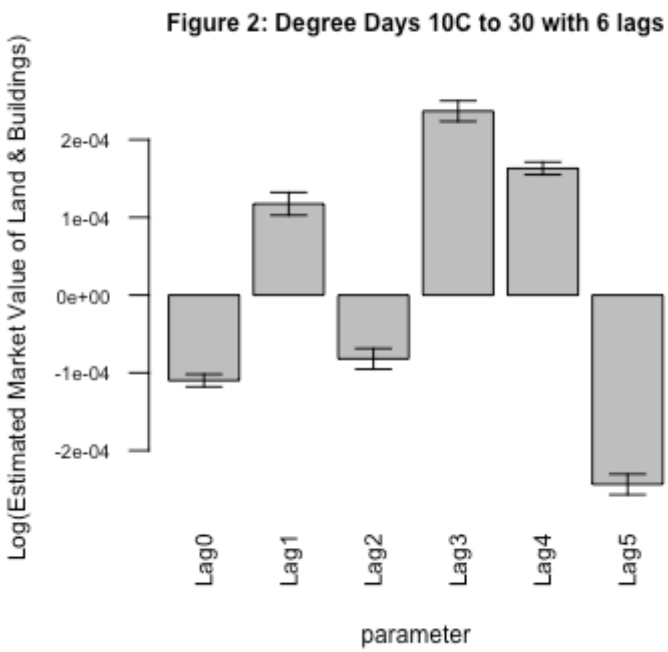
Figure 1 illustrates the effect of lagged Degree Days from 10°C to 30°C on the log of my dependent variable.[11] After graphing my distributed lag model for Degree days 10°C to 30°C (Figure 1), I saw that I needed to increase the number of lags, given that as the number of lags increases, the effect of previous weather should diminish and eventually be exhausted. However, because the lag weights for lags 3 and 4 in Figure 1 were larger than the lag weights for lags 0, 1, or 2, it would seem that there is an underlying problem with my model specification.

Figure 1: Degree Days 10C to 30 with 5 lags

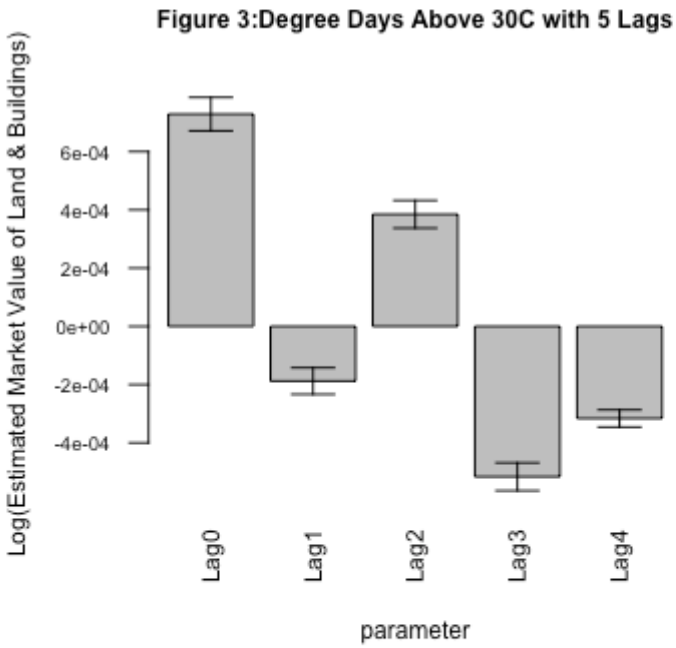


[11] Each Figure corresponds to a fitted regression model for our study period of 1987 through 2002.

Notice in Figure 2 which represents Degree Days 10°C to 30°C, I added an additional lag (Lag 5), and this lag is approaching zero in the expected manner.



Interestingly, in Figure 3 below, which graphs Degree Days Above 30°C, the distribution of lags behaves is approaching zero, and as such I do not feel the need to include a sixth lag.



In Table 2, I report regression coefficients for Degree Day. To test if these lagged weights are statistically significant, I conduct a linear hypothesis test, restricting all β coefficients to sum to zero. For both the 1) Degree Days 10°C to 30°C and 2) Above 30°C degree day variables, I reject the null hypothesis that these parameters sum to zero. The p-values for these linear hypothesis tests are both less than 2.26 $*10^{-16}$. Therefore, there is a permanent effect of weather shocks on farmland values.

Table 2: Selected Statistics from Fitted Regression

Term	Coefficient	Lower (95%) CI	Upper(95%) CI	Robust SE	Naïve SE
Degree Days 10°C to 30 °C	-0.0005496	-0.000600632	-0.000498582	2.09E-05	2.60E-05
Degree Days 10°C to 30 °C(First Lag)	0.00062022	0.00051565	0.000724789	6.63E-05	5.33E-05
Degree Days 10°C to 30 °C(Second Lag)	-0.000500515	-0.000592776	-0.000408254	4.74E-05	4.70E-05
Degree Days 10°C to 30 °C(Third Lag)	0.001544528	0.001452185	0.001636872	5.03E-05	4.71E-05
Degree Days 10°C to 30 °C(Fourth Lag)	0.001230931	0.00117481	0.001287052	2.72E-05	2.86E-05
Degree Days 10°C to 30 °C(Fifth Lag)	-0.001326414	-0.001408771	-0.001244057	5.12E-05	4.20E-05
Degree Days Above 30°C	0.003136296	0.002774187	0.003498406	0.000214481	1.85E-04
Degree Days Above 30°C(First Lag)	-0.000426701	-0.000736493	-0.000116909	0.000146499	1.58E-04
Degree Days Above 30°C(Second Lag)	0.003562193	0.003253834	0.003870553	0.00015625	1.57E-04
Degree Days Above 30°C(Third Lag)	-0.002215207	-0.002527794	-0.001902621	0.000173538	1.59E-04
Degree Days Above 30°C(Fourth Lag)	-0.002749265	-0.002947741	-0.00255079	0.000100525	1.02E-04

Notes: All variables (terms) were found to be statistically significant at the 0.05 level. variables. These terms are fitted over my study period of 1987 to 2002, and represent a panel of 2826 counties. The *Lower(95%)* and *Upper(95%)* Confidence Intervals were calculated from the *Robust Standard Errors,* which are corrected for serial correlation and heteroskedasticity, but not spatial errors or contemporaneous correlation. The *Naïve SE* column represents the original SE as found in our summary statistics of this regression.

Notice that the impact of the lagged degree days on my dependent variable do not occur immediately for either temperature variable. Therefore, I can conclude that in this framework of a finite lagged model, the previous weather events (and weather shocks) do influence the economic agent's updating behavior; that there is a lingering effect of lagged variables on land values.

5.Conclusion

This study seeks to understand whether farmers perceive there to be an imminent impact due to climate change, and whether or not this effect is temporary or permanent, while reducing the vulnerability to omitted variable bias. A common assumption in climate change literature is that farmers are adapted to their local climatic conditions, and choose to carry out the most profitable activities, given the current state of agricultural technology, local soil, and physical constraints (see Mendelsohn et al. 1994; Deschênes and Greenstone 2007; Fisher et al. 2012.)

By utilizing a finite distributed lag approach, and based on the initial results found in the previous section, we can conclude that during this study period and region, farmers appear to be Bayesian learners. Their current valuation of farmland is not only dependent on observed weather in the present time period, but also on previous (lagged) periods as well. Thus there is a permanent effect on land values due to weather shocks. There are number of caveats that go along with these findings. These include the fact that my panel remains unbalanced and that issues of contemporaneous correlation and spatial error persist. Nevertheless, I am enthusiastic about the research done thus far, and firmly believe that once corrected for the above-mentioned issues, my findings will provide fruitful dialogue and discussion at the upcoming conference.

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