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How well do degree days over the growing season capture the effect of climate on farmland values?

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ABSTRACT

Farmland values have traditionally been valued using seasonal temperature and precipitation but degree days over the growing season offer a more compact alternative. We find that degree days and daily temperature are interchangeable over the growing season. However, the impact of degree days in spring and summer is quite different. Climate effects outside the growing season are also significant. Cross sectional evidence suggests seasonal temperature and precipitation are very important whereas temperature extremes have relatively small effects.

1. Introduction

Understanding whether climate change poses a risk to future food supplies is a critical issue for greenhouse gas mitigation. There are three primary tools that shed light on the sensitivity of agriculture to climate change: crop modeling, cross sectional analysis of climate, and panel weather studies. The cross sectional literature and crop studies generally find that warming has a hill-shaped relationship with yields, crop net revenues, and farmland values (see review in Mendelsohn and Dinar, 2009). Cross sectional studies and crop models also find that there are very strong seasonal patterns to how crops respond to climate (Mendelsohn and Dinar, 2009). Schlenker et al. (2006) (SHF) also find a hill-shaped relationship between temperature and farmland values but they argue that only the growing season is relevant. SHF even argue it is not important to distinguish between spring and summer. SHF (and later Fisher et al., 2012) also argue that degree days provide more accurate forecasts of climate impacts than temperature. SHF finally argue that there is a critical threshold at 34 °C above which farmland values precipitously fall. The panel weather literature has adopted many of these assumptions by looking at degree days over the growing season to measure the impacts of climate on agriculture (Schlenker et al., 2006; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007; Fisher et al., 2012; Auffhammer et al., 2013; Moore and Lobell, 2014). There are, however, a few panel studies that recognize the importance of seasons (Welch et al., 2010; Tack et al., 2015). The panel weather studies often find that only high temperatures are harmful. That is, panel weather studies do not capture the harmful effect of cold weather that is seen in cross-sectional studies.

This study tests all of these hypotheses in SHF. To match the original SHF domain, the paper gathers a panel data set of US farms east of the 100th meridian. There were data problems with the climate used in SHF which casts doubt on the empirical results in that paper. For example, SHF state the mean number of degree days above 34 °C is 2.37 and every county had at least some days above 34 °C. However, other climate data sets suggest very high daily temperatures are very rare. For example, the North American Regional Reanalysis (NARR) finds only 0.188 degree days above 34 °C on average, and only 45% of counties had any days above 34 °C. The climate data in Schlenker and Roberts (SR) (2009) suggests there are only 0.004 degree days above 34 °C on average. It therefore seems prudent to re-estimate SHF using more reliable climate data. To address the climate issue, we examine impacts across five alternative climate data sets: NARR (Mesinger et al., 2006), SR (Schlenker and Roberts, 2009), ERA-Interim (Dee et al., 2011),

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GHCN-CAMS (GHC) (Menne et al., 2012), and University of Delaware (UDE) (Matsuura and Willmott, 2012a, 2012b). We include several control variables such as elevation, latitude, soils, access to irrigation water, and market access to control for missing variable bias that were not included in SHF. As Deschênes and Greenstone (2007) argue, it is important to include control variables that are both correlated with climate and farmland value.

The paper tests five hypotheses in SHF. 1) Degree days are more accurate than daily temperature in explaining farmland values. 2) Crops respond the same way to climate in the first half of the growing season (spring) versus the second half (summer). 3) The climate outside the growing season does not affect farmland value. 4) Extreme temperatures have very large effects on farmland values. 5) A growing season model is more accurate than a four season model.

We perform a number of robustness checks in the Appendix. We test the results with and without state fixed effects. We try a number of different functional forms and alternative methods of interpolating climate data. We test five different climate data sets.

The next section of the paper reviews the methodology. Section 3 briefly describes the climate and agricultural data. Section 4 displays the results and the paper concludes with a discussion of the limitations of the research, the main conclusions, and the policy implications.

2. Methodology

This study examines alternative cross sectional (Ricardian) models of the effect of climate on farmland value. The basic underlying model (Mendelsohn et al., 1994) (MNS) has the following form:

$$Y_{i,t} = \boldsymbol{\beta}\, h(C_i) + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t} \tag{1}$$

where Y is the log of land value per hectare for observation i, $h(\cdot)$ is a generic function of the vector of climate variables, C, X is a set of socio-economic variables that vary over time, Z is a set of geographic and soil characteristics that are fixed over time, and ε is assumed to be a random component. The estimated parameters include β, γ, and θ. Farmland values are reported by farmers in the US Census of Agriculture and reflect the purchase value of the farm which includes the land and the structures on the land. In this study, we use an enhanced version of the MNS model that includes additional control variables and time dummies in a pooled regression of land values from six Agricultural Census Years from 1982 to 2007 (Massetti and Mendelsohn, 2011a, 2011b). The relationship between climate (long term average weather) and land values is assumed to be nonlinear. Average daily temperature (average of eight 3-h temperature measurements across 1 day), degree days, and precipitation are introduced in a quadratic fashion.

We test two versions of this model. In the first version, we follow SHF and use the sum of degree days (DD_i) and cumulative rainfall (P_{GS}) over the growing season, from April to September:[1]

$$Y_{i,t} = \beta_0 + \beta_1 DD_{GS,i} + \beta_2 DD_{GS,i}^2 + \beta_3 P_{GS,i} + \beta_4 P_{GS,i}^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t}\,. \tag{2}$$

We test two variations of (2). In the first we sum degree days separately in the first half and the second half of the growing season and we introduce seasonal precipitations. In the second variation we control for the effect of extreme temperature.

In the second version of the model, we use daily temperature averaged over the growing season instead of degree days:

$$Y_{i,t} = \beta_0 + \beta_1 T_{GS,i} + \beta_2 T_{GS,i}^2 + \beta_3 P_{GS,i} + \beta_4 P_{GS,i}^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t}\,, \tag{3}$$

We test two variations of (3). The first uses average temperature and precipitations in the first and second half of the growing season. The second variation is a four season model. The vector of time varying variables $X_{i,t}$ includes time dummies.

We estimate both models (2) and (3) and compare the results. We then test the hypothesis that degree days in the first half of the growing season have the same coefficients as degree days in the second half of the growing season. We make similar tests with the temperature model in the first half versus the second half of the growing season. We compute F test statistics of whether the climate (temperature and precipitation) coefficients are the same in the two halves of the growing season.

We then examine the reported threshold at 34 °C. We compare two measures of this threshold. There is the measure used by SHF, DD34, which is the sum over the growing season of cumulative daily temperatures above 34 °C.[2] We also examine D34 which is the sum of all degree days in days with an average temperature greater than 34 °C.[3]

We compare the out-of-sample forecasting accuracy of the four season model with the forecasting accuracy of: (1) a growing season model with degree days, (2) a growing season model with average temperature and (3) a model that does not control for climate. We draw a random sample of counties and we estimate the four models using three different climate datasets. The coefficients are then used to predict the farmland values in the omitted counties and we calculate the Root Mean Squared Error (RMSE). We repeat this exercise for 1000 random samples. We then execute pairwise *t*-tests of whether the RMSE of predicted land values is the same in the two models. We use sample sizes equal to 70%, 80% and 90% of all counties.

Finally we compare the climate impacts these models suggest for American agriculture east of the 100th meridian for a 2 °C and 4 °C uniform warming.

We weight counties by hectares of farmland to adjust for heteroscedasticity. Throughout the paper we present standard errors corrected for spatial correlation as in (Conley, 1999) using a 300 km radius Bartlett kernel around each county's centroid.[4] We conduct a number of robustness checks to confirm the results. All these robustness tests are summarized in the Appendix.

3. Data

This paper examines five different climate data sets as stated in the Introduction but focuses the presentation on the North American Regional Reanalysis (NARR) data. This data set was constructed by meteorologists using weather station data as well as other measures (such as satellite measures) of North American climate. The dataset provides 3-h temperature on a 32 × 32 km grid from 1979 to present day. We average the eight 3-h temperatures within the day to measure daily temperature and degree days.[5] We utilize the 2 m temperature

[1] Degree days reflect daily temperatures that exceed 8 °C. Following SHF, they are capped at 32 °C although we also test uncapped degree day measures and find no difference in the results. More details are in the Appendix. The degree days are summed from April 1 to September 30.

[2] By denoting with $t_{i,r}$ the daily mean temperature at grid cell i, during day r, $DD34_i$ are calculated as follows: $dd34_{i,r} = t_{i,r} - 34$ if $t_{i,r} > 34$ and $DD34_i = \sum_{r \in \{Apr,\ldots,Sep\}} dd34_{i,r}$, where we have dropped the year index for ease of notation.

[3] $D34_i$ are calculated as follows: $d34_{i,r} = t_{i,r} - 8$ if $t_{i,r} > 34$ and $D34_i = \sum_{r \in \{Apr,\ldots,Sep\}} d34_{i,r}$.

[4] We use the Conley (1999) panel data equivalent algorithm developed by Solomon Hsiang and available at http://www.solomonhsiang.com/computing/stata-code. The covariance matrix estimator is obtained using the inverse distance weighted average of spatial autocovariances that fall within a uniform kernel with a cutoff point set at 300 km. We consider serial correlation over time for two lags (10 years).

[5] Because temperatures within the day are skewed to the right, the average of the eight 3-h temperatures is lower than the average of the minimum and maximum temperature each day. It is important to capture this skew correctly (Tack et al., 2015).