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Is Weather Really Additive in Agricultural Production?

Implications for Climate Change Impacts

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RESOURCES FOR THE FUTURE

Is weather really additive in agricultural production? Implications for climate change impacts

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Abstract

Recent reduced-form econometric models of climate change impacts on agriculture assume climate is additive. This is reflected in climate regressors that are aggregated over several months that include the growing season. In this paper I develop a simple model to show how this assumption imposes implausible characteristics on the production technology that are in serious conflict with the agricultural sciences. I test this assumption using a crop yield model of US corn that accounts for variation in weather at various times of the growing season. Results strongly reject additivity and suggest that weather shocks such as extreme temperatures are particularly detrimental toward the middle of the season around flowering time, in agreement with the natural sciences. I discuss how the additivity assumption tends to underestimate the range of adaptation possibilities available to farmers, thus overstating projected climate change impacts on the sector.

JEL Classification Codes: Q54, Q51, Q12

Keywords: climate change, agriculture, production, additivity

1 Introduction

Agriculture is arguably one of the most researched sectors in the climate change impacts literature. Statistical and econometric approaches have become increasingly popular among economists as alternatives to their earlier biophysical process-based counterpart. These empirical approaches exploit cross-sectional or time variation of observational data to recreate hypothetical counter-factual changes in local climate based on the revealed preference paradigm (e.g., Schlenker, Hanemann and Fisher, 2005; and Deschênes and Greenstone, 2007). The typical approach consists of estimating a reduced-form model capturing the

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sensitivity of agricultural production or welfare to changes in monthly or pluri-monthly climate variables and multiplying the resulting parameters by the predicted changes of climate variables under climate change to derive potential impacts on the sector.

A crucial challenge in this line of research is to choose the right climate variables. This is a difficult task because of the complex interactions of farmer behavior with crop growth and environmental conditions. Weather fluctuates and affects crop growth throughout the growing season and informed farmers adjust the timing and level of inputs accordingly. Attempts to capture too many of these biophysical and behavioral complexities statistically quickly become subject to multicolinearity and spurious correlations (see Kaufmann and Snell, 1997, for a discussion).

Somewhat dichotomous approaches have developed in the literature. In the econometric literature, researchers have made somewhat arbitrary choices of variable types (e.g., precipitation, temperature, soil moisture) and time frames of aggregation (pluri-monthly or monthly averages or totals) with little basis for discrimination other than model fit and parsimony. A more parsimonious model, i.e., with less parameters to estimate, may be chosen because it offers comparable predictive power despite violating agronomic wisdom. This seems to be the case regarding the choice of time frame of aggregation for climate variables in this literature. Alternatively, in the agronomic and agricultural science-based literature, models have been grounded in agronomic principles and agricultural production experiments without considering behavior and revealed preferences of farmers. In practice, these objectives conflict. While agronomic science suggests that environmental conditions have varying effects throughout the season, some of the most influential econometric studies have relied on climate variables aggregated over several months. For instance, the econometric studies of Schlenker, Hanemann and Fisher (2006) and Deschênes and Greenstone (2007) aggregate climate variables over the April-September period while Schlenker and Roberts (2009, henceforth SR) regress crop yields on climate variables aggregated over the March-August (corn and soybeans) and April-October (cotton) periods.

Agriculture is well known to be a time-sensitive activity and pluri-monthly aggregation of weather over the season seems at odds with this fundamental characteristic. This feature is known not only to farmers and agronomists, but also to agricultural economists who have developed production models accounting for the sequential nature of agricultural decision-making process (e.g., Mundlak and Razin, 1971; Antle, 1983). Season-long pluri-monthly windows for weather aggregation imply serious assumptions about the technology and farmers' ability to adapt in the long run. In particular, this choice of variables imposes neutral technical change as well as implausible interactions of weather with endogenous farmer inputs and decisions. It also conceals the potential for farmer adaptation through changes in the timing of the growing season. Although this practice might be innocuous for short-run forecasting purposes, it can have serious consequences for long-term climate change impact analysis.

The purpose of this paper is to explore whether the temporal additivity of weather assumption is valid for agricultural production. This is a prevalent premise in the econometric climate change literature for which consequences have received little attention. In my exposition, I develop a simple theoretical model to explore the implicit assumptions stemming from the adoption of a reduced-form approach and the use of season-long weather variables. By a reduced-form model, I refer to a model that not only excludes the accompanying structure of how decision processes interact with changing technology, but also aggregates some of the processes temporally for the purposes of empirical implementation. For clarity of exposition I focus on reduced-form crop yield models, such as SR, that regress crop yields on weather variables. I then explore this question empirically and test for weather additivity using a 31-year balanced panel of US county-level corn yields representing 70% of US production. Results suggest that weather effects are not additive, and rather that extreme temperatures are particularly detrimental during the middle of the growing season. I then discuss some of the implications of these findings for adaptation and the related shortcomings of assuming additivity of weather in the context of climate change impact analysis.

The paper is organized as follows. In section 2 I develop a simple theoretical model to illustrate the implicit assumptions of time aggregation in reduced-form crop yield models that are widely used in this literature. In section 3 I present an empirical model to explore the effects of these assumptions and discuss the results and implications for climate change impact analysis. Section 4 concludes.

2 Implicit assumptions of weather additivity

To explore the implications of imposing additivity of weather inputs in reduced-form crop yield models, consider an underlying optimization model in which the farmer makes decisions sequentially during the season. Input decisions in a stage of the growing season $s = \{1, ..., S\}$ are made with uncertainty about future weather and are conditioned on decisions already made as well as weather already observed. Assume a risk-neutral farmer. The expected profit maximization problem is:

$$\max_{x_{ts}} E_s \left[p_t y_t - \sum_{j=1}^{s} r_{tj} x_{tj} - \sum_{j=s+1}^{S} r_{tj} x^*_{tj}(x_{ts}) \mid w_{t1}, ..., w_{t,s-1}, x_{t1}, ..., x_{t,s-1} \right] \tag{1}$$

subject to

$$y_t = f_t \left(x_{t1}, ..., x_{tS}, w_{t1}, ..., w_{tS} \right) + \epsilon_t \tag{2}$$

where E_s represents an expectation at the beginning of crop stage s, input price vectors r_{tj} apply to input vectors x_{tj} chosen at each growing stage j, output price p_t applies to yield y_t, which depends on variation in weather w_{ti} as well as input decisions x_{tj} that apply through the various stages of the growing season. $x^*_{tj}(x_{ts})$ represents the optimal input decision vector at future stages given input decisions at all prior production stages $x_{t1},...,x_{t,s-1}$ and all prior observed weather $w_{t1},...,w_{t,s-1}$ during the growing season as well as the current decision x_{ts} at stage s assuming all future decisions will be made optimally given further weather realizations. Yield can be represented generally as shown in (2) where ϵ_t is a random error in production.

Changing Technology

The technology denoted by f_t must be considered as changing over time t for the long-run nature of climate change analysis. If output price and yield are considered uncorrelated at the individual farmer level and the output price expectation does not vary with the crop stage (for conceptual simplicity), then the first-order conditions for (1) after substituting (2) are:

$$E(p_t)\frac{\partial}{\partial x_{ts}}E\left[f_t\left(x_{t1},...,x_{t,s-1},x_{ts},x^*_{t,s+1},...,x^*_{tS},w_{t1},...,w_{tS}\mid w_{t1},...,w_{t,s-1},x_{t1},...,x_{t,s-1}\right)\right]-r_{ts}=0 \quad (3)$$

Clearly, this optimization process, which is solved by backwardation, causes input decisions at stage s to depend on weather variables at prior stages $w_{t1},...,w_{t,s-1}$. This is a direct theoretical reason why interactions among weather and input decisions arises. Further, input decisions and weather variables could also be correlated because some input decisions can affect vulnerability of crops to future weather during the growing season (see Just and Pope, 1979).

Correlation of Input Choices and Weather

Yield is a central component of farmer profit and therefore an important channel for analyzing climate change impacts. The literature readily recognizes that accuracy of climate change impact assessments for agriculture depends on representing yield impacts correctly. While representing the full complexity of this decision model is impractical, a first approximation of the crop yield model implied by this optimization problem might be represented as:

$$y_t = T_t\alpha + X_t\beta + W_t\gamma + Z_t\delta + \epsilon_t \quad \text{(Model 1)}$$

where $T_t = [1, t]$, $X_t = [g(x_{t1}), \ldots, g(x_{tS})]$, $W_t = [h(w_{t1}), \ldots, h(w_{tS})]$, and Z_t is a vector of functions of applicable interaction terms among and between input decisions and weather. The g and h functions represent nonlinear effects of inputs and weather variables, respectively. For instance, the functional form of h could capture well-known detrimental effects on crop yield of high temperatures and extreme precipitation levels.

In contrast, however, standard practice in the literature omits farmer inputs and interactions, which reduces Model 1 to a further simplified form,

$$y_t = T_t\alpha^* + W_t\gamma^* + u_t \tag{Model 2}$$

where the constant term in α^* is implicitly modified by $\bar{X}\beta + \bar{Z}\delta$ and the error term implicitly represents $u_t = X_t\beta - \bar{X}\beta + Z_t\delta - \bar{Z}\delta + \epsilon_t$. This simplification, however, can severely bias estimates of the γ^* parameters that are used to assess the impacts of climate change. The reason is that weather variables are correlated with the omitted input variables and with the interactions of terms among and between input and weather variables.

One reason economists in this field have been willing to use highly approximating specifications is that the interest is not in unbiased estimates of γ, but in unbiased long-run yield forecasts $\Delta y = \Delta W\gamma^*$. However, such forecasts based on Model 2 assume that the correlation between W_t and u_t remains unchanged as climate change occurs. In other words, W_t functions as a proxy not only for weather conditions but also for correlated farmer behavior. This assumption is violated if the conditioning of optimal input choices on previous input decisions and weather $x^*_{ts}(x_{t1}, ..., x_{t,s-1}, w_{t1}, ..., w_{t,s-1})$ changes. This means that if the correlation of the proxy with the omitted variable of interest changes in the forecasting period then forecasts are biased. This can occur for various reasons.

Non-neutral Technical Change

First, Model 2 imposes neutral technical change. This is problematic for assessing climate change effects because the parameters in γ^* are likely functions of t. This would alter the optimal choice x^*_{ts} and thus change the correlation between W_t and u_t, which would bias forecasts. This also occurs when technical change is induced by climate change, which would make γ a function of long-run climate.[1] Second, changes in relative prices can lead to changes in optimal input use as shown in (3). Such changes may be major over

[1] It is possible to allow γ^* to vary over time (e.g., Roberts and Schlenker, 2011) but estimates are inevitably confounded with potential time trends in β. For instance, if inputs are becoming more productive (increasing β) but make crops more vulnerable to weather shocks ($\delta < 0$), γ^* may well appear as becoming more detrimental over time despite γ and δ actually remaining unchanged.

a long time period, and thus introduce an additional source of bias for long-run yield projections.

Weather Aggregation Bias

Another simplification in most econometric studies of climate change analysis is to use season-long measures of weather. For US corn a common period is March to August because it spans the full growing season for most producing regions. This practice imposes the same γ parameters on weather variables in all stages of crop growth in the same season:

$$y_t = T_t\alpha^* + h\left(\sum_{j=1}^{S} w_{tj}\right)\bar{\gamma} + v_t \qquad \text{(Model 3)}$$

where the number of parameters in γ^* is reduced by a factor of S to obtain $\bar{\gamma}$ and the error term is implicitly further modified to $v_t = \sum_{j=1}^{S}\left(h(w_{tj}) - h(\bar{w}_j)\right)\gamma + X_t\beta - \bar{X}\beta + Z_t\delta - \bar{Z}\delta + \epsilon_t$.[2] This third model assumes $[h(w_{t1}), \ldots, h(w_{tS})]\,\gamma^* = h\left(\sum_{j=1}^{S} w_{tj}\right)\bar{\gamma}$, which assumes h is factor-wise separable. This implies that weather realizations $w_{t1}, ..., w_{tS}$ are perfect substitutes within the growing season. However, this assumption is in serious conflict with evidence from the agricultural sciences.

Aggregation of weather effects throughout the growing season can be very misleading. Extreme weather events are not equally likely across stages of the growing season. Many crops across the Midwest are planted in the spring and harvested in the fall when temperatures are cooler. The middle of the season, which includes the sensitive flowering stage, typically occurs in the summer months when extreme temperatures are more prevalent. As a result temperature shocks aggregated over the entire season may appear to be detrimental to *all* crop stages, rather than to the most sensitive stages of crop growth.

Moreover, the model also presumes that the correlation between season-long weather variable $h\left(\sum_{j=1}^{S} w_{tj}\right)$ and the unexplained residual v_t would remain constant under climate change. Given the underlying model in (1) is sequential, this presumes the first-order conditions in (3) remain unchanged for any sequence of weather variables $w_{t1}, ..., w_{t,s-1}$ with the same sum, that is,

$$\begin{aligned} & \frac{\partial}{\partial x_{ts}} E\left[f_t\left(x_{t1}, ..., x_{t,s-1}, x_{ts}, x^*_{t,s+1}, ..., x^*_{tS}, w_{t1}, ..., w_{tS} \mid w_{t1}, ..., w_{t,s-1}, x_{t1}, ..., x_{t,s-1}\right)\right] \\ = & \frac{\partial}{\partial x_{ts}} E\left[f_t\left(x_{t1}, ..., x_{t,s-1}, x_{ts}, x^*_{t,s+1}, ..., x^*_{tS}, w_{t1}, ..., w_{tS} \mid \sum_{j=1}^{s-1} w_{tj}, x_{t1}, ..., x_{t,s-1}\right)\right] \end{aligned}$$

which suggests no interactions among and between weather and endogenous inputs across stages. As an illustration, this suggests that farmers would time fertilizer, pesticide, and irrigation applications indepen-

[2] The expression in Model 3 can be easily adapted to allow season-long averages of weather variables.

Table 1: Characteristics of yield models

Model	Specification	Error term	Inputs β	Weather γ	Interactions δ
1	$y_t = T_t\alpha + X_t\beta + W_t\gamma + Z_t\delta + \epsilon_t$	$\epsilon_t \overset{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$	U	U	U
2	$y_t = T_t\alpha^* + W_t\gamma^* + u_t$	$u_t = X_t\beta - \bar{X}\beta + Z_t\delta - \bar{Z}\delta + \epsilon_t$	C	U	C
3	$y_t = T_t\alpha^* + h\left(\sum_{j=1}^{S} w_{tj}\right)\bar{\gamma} + v_t$	$v_t = \sum_{j=1}^{S}\left(h(w_{tj}) - h(\bar{w}_j)\right)\gamma + u_t$	C	E	C+E

U: Parameters are unrestricted; C: Parameters are constant over time but may differ across stages; E: Parameters are equal across stages.

dently from weather. This is obviously incorrect. The preeminent role of weather forecasts in agricultural production constitutes a clear counterexample.

Summary

Table 1 summarizes the key points of this section. Yield forecasts under climate change based on all three models assume constant relative prices, a likely artifact of the unpredictability of relative prices far in the future. Model 1 can accommodate more general forms of technical change than Model 2, but both Models 1 and 2 impose neutral technical change. In that sense, Model 1 has wider applicability as it allows the exploration of interactive effects of weather and endogenous farmer inputs. This could include analysis of input uses that attenuate vulnerability to weather shocks.

However, such farmer behavior is generally poorly observed. Model 2 offers an alternative specification that omits farmer inputs and interaction effects. This model presents a somewhat flexible form to explore implicitly the potential changes in yield with varying effects throughout the season. However, because the functional form assumes neutral technical change, input and interactive parameters are assumed to remain constant over the sample and forecasting periods.

Model 3, which is the widely used specification in the literature, imposes additive weather and thus implies equal marginal productivities of weather as well as equal interactive effects of weather with endogenous inputs across all season stages. This is in addition to assuming constant weather and interactive parameters as for Model 2. To explore the validity of the additivity assumption in Model 3, I rely on Model 2 and test for equality of parameters across stages. I develop an empirical model for this purpose in the next section.

3 Empirical exploration

Data

To explore the assumption of weather additivity in crop yield models requires matching data on weather conditions with crop progress at various times over the growing season in each location. The highly detailed weather data used in this paper is based on the North American Land Data Assimilation System (NLDAS) , which is a joint project of the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), Princeton University, and the University of Washington. The NLDAS weather dataset features hourly and 14-km resolution and has been shown to closely match observations of highly precise weather stations in the Great Plains (Cosgrove et al., 2003). These data thus allow considerable local specificity. For instance, Indiana, which has the lowest average county size in the Midwest (1,025 km^2), includes over five NLDAS grids per county on average.

Agricultural data are obtained from the US Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). Because corn production data are available only at the county level, the hourly gridded weather data must be spatially aggregated for each county. I do so by weighting each NLDAS data grid within a county by the amount of cropland within each grid. The cropland area is derived from the USDA-NASS's 2011 Cropland Data Layer which has a 30-meter resolution. This allows weighting NLDAS data grids according to the amount of farmland they include in constructing the county-level observations. Hourly observations were subsequently used to construct exposure to individual degree bins for the March-August period for each year and county.

Because rainfed and irrigated corn yields are expected to respond differently to exogenous environmental conditions, their respective parameters are estimated separately. For this purpose, I restrict the sample to counties where at least 75% of the acreage, on average, is rainfed. Figure 1 illustrates where the sample counties are located. The dataset corresponds to a balanced corn yield panel of 800 Midwest rainfed counties for 1981-2011, which represents 70% of US corn production.

My major focus in this paper is to evaluate the validity of time aggregation of weather variables throughout the growing season. In order to do so, I account for variation in weather conditions throughout the growing season. This allows estimation of possible varying effects from intra-seasonal environmental conditions on crop yield. Accounting for the timing effect using standard agronomic principles requires information on crop stages. I thus rely on the Crop Progress and Condition weekly survey by USDA-NASS which provides state-level data on farmer activities and crop phenological stages from early April to late November. Reporting across states and years is not balanced. Although state reports date back to 1979, reporting for corn that includes both the onset (planting/emergence) and the end of the season (maturation/harvesting) begins in

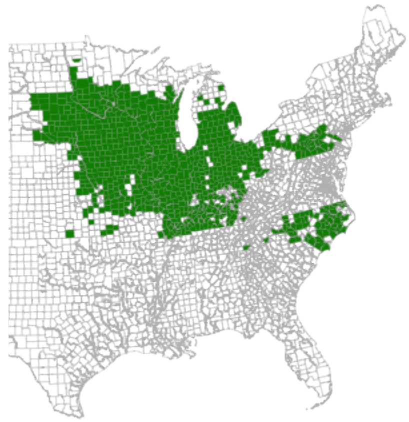

Figure 1: Rainfed counties in the sample

1981 for the major producing states.

Specifically, this survey reports the percentage of a state's corn acreage undergoing certain farming practices and reaching specific crop stages.[3] As a consequence, it does not offer clear "boundary" dates between stages because of the timing variations within states.[4] For the purpose of defining such boundaries of the growing season for each county, I obtain stage median acreage dates. These correspond to the dates at which 50% of the acreage in a given state has reached each stage in a given year.[5]

Crop stages reported by the USDA are not equally spaced in the growing season. They arguably correspond to visible markers that can be easily verified to simplify data collection. Some past studies (e.g., Kaufmann and Snell, 1997) have relied on weather variables matched to precise crop stages. However, results are sometimes difficult to interpret, especially for non-agronomists. In order to convey a more accessible crop advancement metric, I divide the growing season into eight segments centered around flowering (i.e., silking), which is considered the midpoint of the season. Four equally spaced periods occur in the vegetative phase (between planting and silking) and four equally spaced periods occur in the reproductive or grain-filling phase (between silking and maturation). For simplification, the crop advancement division is converted into percentages with intervals of 12.5%. Thus, the 0-12.5% and 87.5-100% stages correspond, respectively, to the first and last segments just after planting and just before maturation, and the 37.5-50% and 50-62.5%

[3]The report includes progress of farming activities (planting and harvesting) and of corn phenological stages (emerged, silking, doughing, dented, and mature). The USDA defines these crop stages as follows. Emerged: as soon as the plants are visible. Silking: the emergence of silk-like strands from the end of corn ears, which occurs approximately 10 days after the tassel first begins to emerge from the sheath or 2-4 days after the tassel has emerged. Doughing: normally half of the kernels are showing dents with some thick or dough-like substance in all kernels. Dented: occurs when all kernels are fully dented, and the ear is firm and solid, and there is no milk present in most kernels. Mature: plant is considered safe from frost and corn is about ready to harvest with shucks opening, and there is no green foliage present.

[4]Visual inspection of district-level crop progress reports, which are available for only a few states, surprisingly reveals variation similar to overall state progress for most years.

[5]For a few states and years, crop progress reporting began too late (the state had already surpassed the 50% acreage level) or stopped too early (the state had not yet reached the 50% acreage level). For these cases, which represent less than 5% of the cases, I obtained the median acreage date by extrapolation.

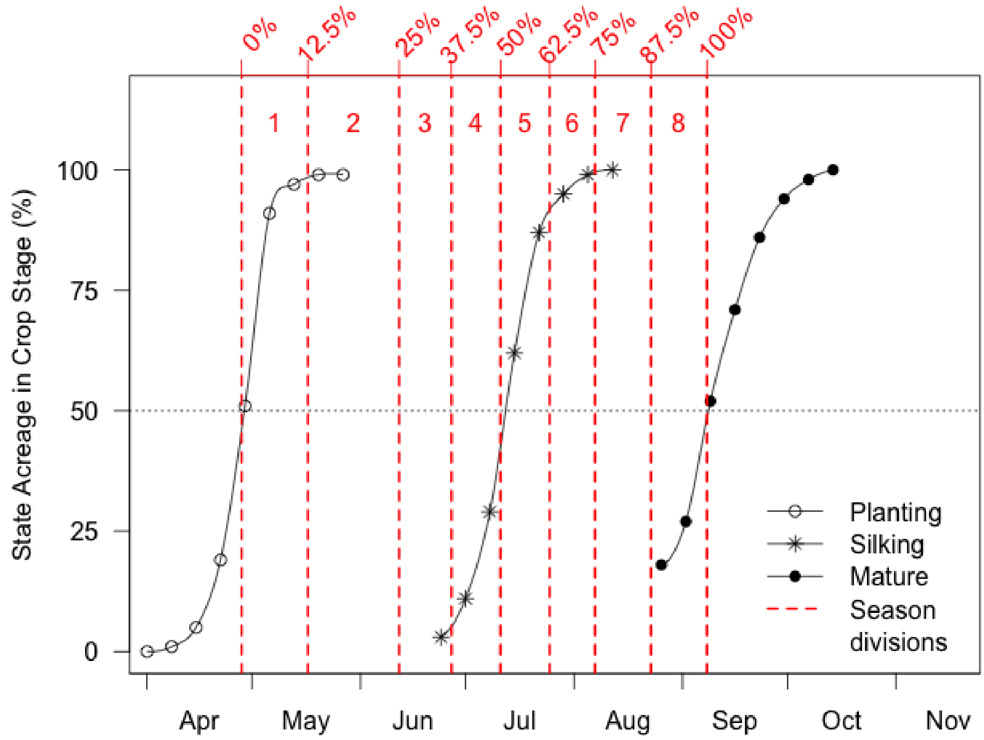

Figure 2: Season divisions for Illinois corn in 2001

stages correspond, respectively, to the segments just before and just after flowering.

Natural scientists have found that crop development or phenology is proportional to accumulated growing degree days (GDD; see, e.g., Hodges (1991); Smith and Hamel (1999); Fageria, Baligar and Clark (2006); Hudson and Keatley (2009)). This variable is defined by the area under the temperature-time curve that falls between two temperature thresholds (10 and 30ºC for corn) during a given period of time. Warmer conditions generally lead to faster GDD accumulation and more rapid crop development. This concept can be used to split the growing season into equally spaced segments.

Following this approach, I compute a cumulative GDD variable starting at planting for each state and year and use it to represent the eight segments of the season. Figure 2 illustrates how the 2001 calendar for Illinois can be broken down into seasonal segments . Although the segments have a different numbers of days, segments 1-4 and 5-8 are equally spaced in terms of GDD. Thus, wider segments signal slower development due to cooler conditions.

Exposure to temperature bins is aggregated within each of these segments. As a result, the temperature variables account for exposure to different temperature levels during the eight individual segments of the growing season. This allows assessment of how sensitivity to temperature varies with crop advancement. Finally, because exposure to some temperature levels is low or nonexistent for some crop stages, I aggregate

Table 2: Summary statistics of weather variables by stage

Stage	1	2	3	4	5	6	7	8	1 - 8
Advancement (%)	0-12.5	12.5-25	25-37.5	37.5-50	50-62.5	62.5-75	75-87.5	87.5-100	0-100
Length (days)	25.1	17.2	15.1	13.9	13.1	13.0	13.9	18.9	130.0
Precipitation (mm)	90.4	65.6	52.6	48.9	42.4	40.4	43.7	55.9	439.8
Exposure (hours)									
0-10ºC	58.8	0.0	0.0	0.0	0.0	0.0	0.0	35.5	94.2
10-20ºC	330.9	147.8	85.0	61.9	58.6	71.7	96.0	203.2	1055.1
20-30ºC	208.4	245.5	246.0	232.7	214.0	201.5	200.3	189.2	1737.8
⩾30ºC	9.5	31.2	45.9	53.9	55.6	53.0	49.7	34.2	332.9

bins at the extremes that do not represent more than 0.15% of the growing season on average over the sample period.

The summary statistics for each stage are presented in table 2. As expected, the early and late parts of the season are slightly longer in terms of days. Total average precipitation by stage is fairly even when adjusting for crop stage length. Also, exposure to low (high) temperatures is more likely in the extreme (middle) parts of the season. This point should be kept in mind when assessing the effects of extreme temperature on crop yields. It is clear that exposure to high temperature (⩾30ºC) is considerably greaterer on average for stages 4 through 7, spanning the middle of the season when corn flowering occurs.

Model

In this section I present an empirical version of Model 2 to test for weather additivity throughout the growing season. The model approximates the reduced-form crop yield model in SR, which introduced an innovative approach to estimate the effect of exposure to different levels of temperature on yield separately using temperature bins. A key characteristic of their study is that the exposure to different temperature levels is computed during the entire season (March-August for corn). Thus, their estimated model uses season-long weather variables as in Model 3. To generalize to the case of Model 2, I relax the additivity assumption and explore different response functions throughout the growing season.

While the SR model assumes that temperature effects on yield are cumulative and substitutable over time, the nonlinear effects of temperature on yield are captured by the function $h(w)$ representing "yield growth" that depends on temperature w. Function h is obviously homologous to the function by the same name presented in the theoretical section. Logged corn yield y_{it} in county i and year t is represented as:

$$y_{it} = \int_{\underline{w}}^{\overline{w}} h(w)\phi_{it}(w)dw + p_{it}\gamma_1 + p_{it}^2\gamma_2 + z_{it}\alpha + c_i + \epsilon_{it} \tag{4}$$

where $\phi_{it}(w)$ is the time distribution of temperature (i.e., the temperature-time path) for March-August, p_{it}

is precipitation, z_{it} is a state-specific quadratic time trend, andc_i is county fixed effects. In order to relax the additivity assumption I allow h, γ_1, and γ_2 to vary within the growing season. The following model introduces this flexibility:

$$y_{it} = \int_{\underline{s}}^{\overline{s}} \int_{\underline{w}}^{\overline{w}} h(w,s)\phi_{it}(w,s) + p_{it}(s)\gamma_1(s) + p_{it}^2(s)\gamma_2(s)dwds + z_{it}\alpha + c_i + \epsilon_{it} \tag{5}$$

where $\phi_{it}(w,s)$ is the time distribution of temperature at each stage of the season s. Note that s indicates the advancement of the growing season for a given year and location. Equation (5) cannot be estimated directly because of the double integral. Therefore, I follow an approach similar to that of SR and approximate the integral as a sum according to four alternative approaches: a step function allowing different effects at each 1ºC interval (S1), a step function allowing different effects at 3ºC intervals (S2), an eighth-degree polynomial (S3), and a cubic B-spline with eight degrees of freedom (S4). This is done for each of the eight stages of the season. The specification for S1 is:

$$y_{it} = \sum_{s=1}^{8} \sum_{w=0}^{40} \underbrace{h(w+0.5,s)}_{\gamma_{ws}^h}[\Phi_{it}(w+1,s) - \Phi_{it}(w,s)] + p_{its}\gamma_{1s} + p_{its}^2\gamma_{2s} + z_{it}\alpha + c_i + \epsilon_{it} \tag{6}$$

where $\Phi_{it}(w,s)$ is the cumulative time in temperature bin w in county i and year t in stage s.[6] Specifications for S2, S3, and S4 are provided in the appendix. Because unobserved explanatory factors are likely to be spatially correlated, I account for spatial correlation of the errors in the estimation.

Results

Figure 3 presents the temperature response function for each stage of the growing season. There is agreement between the four specifications for each individual stage, although some discrepancies can be perceived at extreme temperature values. The most important result is that the response functions clearly differ by stage of the growing season. For instance, exposure to temperatures exceeding 30ºC have detrimental effects on crop yield toward the middle of the growing period (i.e., 37.5-50%) but not toward the end of the season (i.e., 87.5-100%). This confirms wisdom from the agricultural sciences that crop growth around the flowering stage of corn is the most sensitive to environmental stress. Note that temperature response functions do not extend over the same range of temperatures for all stages (e.g., they do not extend to temperatures higher than 30ºC for the 0-12.5% stage). This is due to a lack of observations of extreme values at some stages of

[6] Note that because some temperature levels do not occur in some stages, the associated parameters are not estimated. For instance, $h(0.5, s=5) = 0$, because a temperature around 0ºC never occurs in the fifth stage, and thus the associated parameter $\gamma_{0,5}^h$ is not estimated.

the growing season.

I performed a simultaneous test of equality of weather parameters across stages for both temperature and precipitation effects to confirm the visual differences.[7] An asymptotic chi-square test rejects equality of parameters across stages with p-values below 2×10^{-16}. Thus there is strong evidence that both the temperature and precipitation response functions vary throughout the season.

These generalizations have important implications for climate change impact analysis. If climate change is particularly detrimental through increased exposure to very high temperatures, then this type of weather shock is more likely to occur in the summer, which is roughly around the middle of the current growing season for corn in the Midwest. As figure 3 reveals, extreme temperature is more damaging toward the middle of the season. As a consequence, in the presence of climate change with an increase in the frequency of high temperatures, farmers would be able to shift the growing season. A shift of even a few weeks can be sufficient to reduce exposure during the most heat-sensitive stages of growth. Some part of the growing season would still be affected by extreme temperature, but the detrimental effects would be reduced. This type of adaptation scenario is made possible when weather is treated as non-additive. Ortiz-Bobea and Just (2013) explore this possibility and show sizable benefits for farmers of changing the timing of the growing season through changes in planting dates.

On the other hand, models that impose additivity of weather imply much more limited possibilities for adaptation. The reason is that shifting the growing season does not lead to any sizable estimated benefit because weather shocks are assumed to have the same effects over all parts of the growing season. This is particularly relevant when considering that climate change is expected to change intra-seasonal climate patterns.

4 Conclusion

One of the crucial challenges in empirical studies that assess the potential impacts of climate change on agriculture is the choice of the right climate variables. A common practice in this literature is to rely on season-long variables because it leads to parsimonious models with relatively high levels of statistical fit. In contrast, this paper shows that the underlying assumption of this approach is invalid. While a reduced-form model with non-additive weather may provide some insights into how production might change in response to a change in climate, the additional assumption of weather additivity introduces strong restrictions that

[7] The test was conducted for both step function specifications which, offer clear parameter equivalence across stages. The spline and polynomial specifications have eight parameters per stage but are defined over different temperature ranges which, does not allow for comparing these eight parameters directly across stages in a meaningful way.

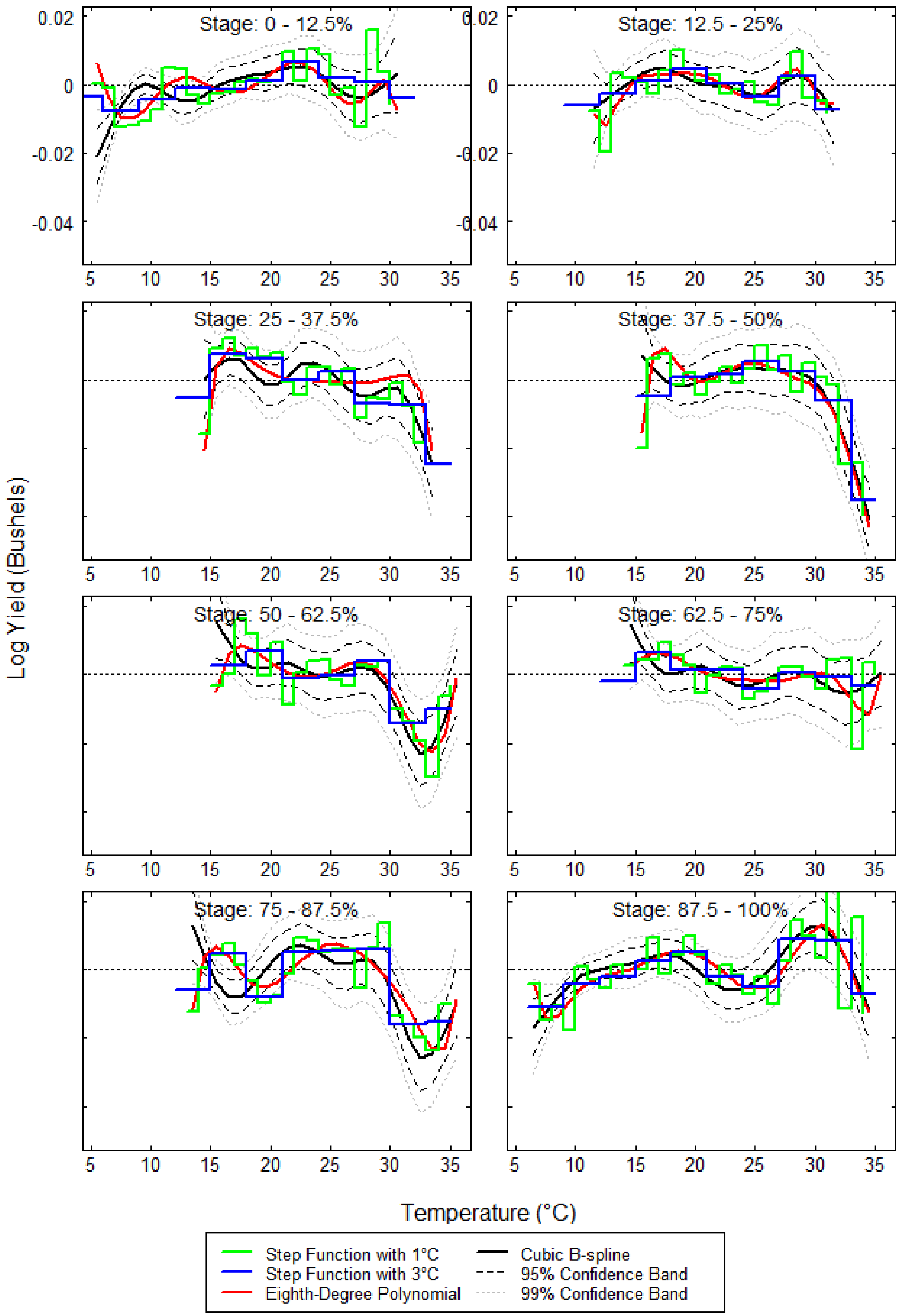

Figure 3: Temperature response by stage

are at odds with the accepted wisdom of agronomic science. It is assumed not only that all marginal productivities of weather variables are equal across stages of crop growth, and that weather variables are perfect substitutes among states, but also that the interaction with time-sensitive endogenous inputs (e.g., fertilizer and pesticides) is constant no matter when the weather input is realized. This latter point would imply that farmers do not rely on weather forecasts for adjusting the timing of input decisions, which is obviously incorrect.

Based on an empirical analysis of US corn yields, I show that both temperature and precipitation effects statistically differ across stages. Results strongly reject the additivity assumption. Crop yield is shown to be especially sensitive to temperatures exceeding 30ºC toward the middle of the season during the flowering period. The same temperature levels do not seem to affect yield when they occur close to the end of the season at maturation time.

Relaxing the additivity assumption in this literature can open the door to assessment of a richer set of adaptation possibilities. Climate change impact studies that restrict the range of farmer adaptation will inevitably overestimate potential costs. In that sense results stemming from current yield models are pessimistic.

Appendix

The specification for the model with a step function allowing different effects at each 3ºC interval (S2) is:

$$y_{it} = \sum_{s=1}^{8} \sum_{w=0,3,6,9...}^{39} \gamma_{ws}^{h} \underbrace{\left[\Phi_{it}(w+3,s) - \Phi_{it}(w,s)\right]}_{x_{its,h}} + p_{its}\gamma_{1s} + p_{its}^{2}\gamma_{2s} + z_{it}\alpha + c_i + \epsilon_{it}$$

The model effectively regresses yield on the time spent within each interval in a given county and year $x_{its,h}$.

Model S3 assumes that the "yield growth" function $h(w)$ is an eighth-degree polynomial of the form $h(w,s) = \sum_{k=1}^{8} \gamma_{ks}^{h} T_{ks}(w)$ where where $T_k()$ is the kth order Chebyshev polynomial. The h superscript in γ simply differentiates temperature parameters from precipitation parameters. Replacing $g(h)$ with this expression yields:

$$
\begin{aligned}
y_{it} &= \sum_{s=1}^{8}\sum_{w=-1}^{39}\sum_{k=1}^{8}\gamma_{ks}^{h}T_{ks}(w+0.5,s)[\Phi_{it}(w+1,s)-\Phi_{it}(w,s)]+p_{its}\gamma_{1s}+p_{its}^{2}\gamma_{2s}+z_{it}\alpha+c_i+\epsilon_{it} \\
&= \sum_{s=1}^{8}\sum_{k=1}^{8}\gamma_{ks}^{h}\underbrace{\sum_{w=-1}^{39}T_{ks}(w+0.5,s)[\Phi_{it}(w+1,s)-\Phi_{it}(w,s)]}_{x_{its,k}}+p_{its}\gamma_{1s}+p_{its}^{2}\gamma_{2s}+z_{it}\alpha+c_i+\epsilon_{it}
\end{aligned}
$$

The model effectively regresses yield on eight temperature variables $x_{its,k}$, which represent the kth-order Chebyshev polynomial evaluated at each temperature bin.

In a similar fashion, model S4 assumes that $h(w,s)=\sum_{k=1}^{8}\gamma_{ks}S_{ks}^{3}(w)$ where $S_k^3()$ is the piece-wise cubic polynomial evaluated for each jth interval defined by eight control points:

$$
y_{it}=\sum_{s=1}^{8}\sum_{k=1}^{8}\gamma_{ks}^{h}\underbrace{\sum_{w=-1}^{39}S_{ks}(w+0.5,s)[\Phi_{it}(w+1,s)-\Phi_{it}(w,s)]}_{x_{its,k}}+p_{its}\gamma_{1s}+p_{its}^{2}\gamma_{2s}+z_{it}\alpha+c_i+\epsilon_{it}
$$

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