Modeling the Structure of Adaptation in Climate Change Impact Assessment

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While a major focus of econometric climate impact assessments on agriculture has been prediction of overall impacts, future research should identify impact mechanisms and adaptation possibilities. Clarifying specific adaptation possibilities facilitates not only the assessment of potential welfare impacts, but also offers the possibility of evaluating policies for improved adaptation. This depends on capturing mechanisms that provide farmers' abilities to adapt to new climatic constraints in counter-factual conditions.

These impact mechanisms are represented with elaborate detail in agronomic crop models that convey the science of crop production. However, the agronomic models are not well integrated with revealed preferences (e.g., Adams 1989, Adams et al. 1990, Easterling et al. 1992, Rosenzweig and Parry 1994). Thus, congruence of agronomic adaptation possibilities with economic behavior that might be observed in counterfactual circumstances is open to question.

Econometric methods have attempted to represent adaptation implicitly by estimating reduced-form relationships between economic variables and arbitrary forms of aggregate weather measures. Leading examples include the Ricardian approach based on cross-section regression of land prices on weather variables (Mendelsohn, Nordhaus, and Shaw 1994 and Schlenker, Hanemann, and Fisher 2005, henceforth MNS and SHF) and the profit panel approach consisting of fixed-effects regressions of net annual revenue on weather variables (Deschênes and Greenstone 2007, henceforth DG). Thus, modeling shortcuts have been used to assess potential impacts of exogenous weather variation without modeling decision-making and adaptive innovation explicitly, and without consideration of the specific weather variables of importance in the science of crop production. Therefore, land prices and observed net revenues may capture farmers' optimal adaptive behavior with an unknown degree of imperfection.

While these highly reduced-form approaches have provided first-cut estimates of climate effects, they do not reflect the mechanisms through which impacts occur, which calls into question the feasibility of predicted adaptive behavior as well as robustness to omitted variables bias. Aggregated approaches also prevent identification of structural relationships necessary to consider adaptation policy assessment and cross-validation.

Recently, research using the econometric approach has focused increasingly on impact mechanisms partly as a means of validating results from reduced-form approaches. This includes renewed interest in statistical yield models (e.g., Schlenker and Roberts 2009, Lobell and Burke 2010) because crop yields represent major mechanisms through which higher temperatures may affect producer welfare. However, most yield models rely on season-long weather variables that overlook the varying sensitivity of crops during the growing cycle, and implicitly assume that growing seasons remain fixed.

Under-representation of flexibility causes overestimation of yield impacts. An example is estimation of heat effects ignoring the flexibility offered by lengthening of the growing season. Conventional agronomic wisdom established through field trials on annual crops is that stress during the relatively short flowering period reduces yield more than in any other stage of growth (Fageria, Baligar,

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and Clark 2006, p. 89). This phenomenon is substantial and statistically significant in US county corn yields (Ortiz-Bobea 2011). Thus, a longer season may allow flexibility to shift the flowering period away from a hotter traditional flowering period. This flexibility is ignored by typical econometric approaches, although common in the agronomic models. Other research has considered the agronomic analysis of agricultural zones (Newman 1980, Adams et al. 1990, Kaiser et al. 1993) by considering potential changes in crop mix using multinomial logit models (Mendelsohn and Dinar 2009, ch. 5). However, these possibilities are typically considered separately rather than jointly. Of course, capturing all adaptation possibilities is a daunting task given the diversity of agriculture. But accounting for major and obvious adaptation strategies based on revealed preferences provides a critical foundation for adaptation policy analysis. Preliminary work, including Ortiz-Bobea (2012) and an example in this paper, implies that climate change assessment should not stop short of exploring these possibilities.

A Structural Approach

This paper proposes an econometric framework for assessing potential impacts of climate change on agriculture that tractably unpacks some of the major impact mechanisms. Following the implicit definition in other empirical work, we define climate as the probability distribution of all aspects of weather relevant to a particular period of time, but (i) define the relevant weather variables for our problem based on scientific knowledge of the underlying mechanisms of production, and (ii) use a behavioral model as an empirical underpinning to capture adaptation given those mechanisms. The key element is the explicit treatment of climate change within a classical constrained optimization framework given potential adaptive private and public actions. In this paper, we consider only the simple behavioral model of profit maximization, but more general applications based on revealed preferences are planned.

As an example, higher temperatures lead to the detrimental effects of hotter summers, but also lengthen the frost-free period, offering farmers the option of longer-season cultivars, different crops, or even relay cropping. Only by a disaggregated approach can the potentially dominating mechanisms of both the detrimental and beneficial aspects of climate change be revealed. And only by combining agronomic knowledge with revealed preferences can these potential counter-factual mechanisms be properly assessed. In addition, this approach can serve to cross-validate qualitatively conflicting results of current leading econometric approaches (see SHF and DG).

For structural modeling, our proposed approach, like most others, presumes prior knowledge of the distribution of climatic inputs and the major climatic constraints imposed by climate change. Specifically, climatic inputs are characterized by the timing and level of their exogenous supply. Climatic constraints arise when the supply of climatic inputs render production infeasible. An example is the time of onset of the growing season which is driven by the last spring frost in the American Midwest. Adequate models must determine whether each constraint is binding in each locality and how its variation contributes to welfare (i.e., to each constraint's shadow price). A disaggregated approach can determine the significance of individual aspects of climate change and their geographic distribution. Shadow prices can then guide investment in adaptation research and related public policy, both topically and financially.

We focus on careful treatment of the physical role of weather variables in production as understood in the production sciences. For example, farmers in temperate US regions choose cultivars that reach maturity before fall frosts because freezing temperatures damage non-mature crops and result in significant yield loss. Reduced-form models attempt to capture this effect through correlations with weather variables such as average October temperature (MNS) or April-to-September growing degree-days (SHF, DG). However, arbitrary calendar variables are likely correlated (imperfectly) with relevant omitted factors, blurring their interpretation for adaptation policy analysis. In contrast, our approach is to rely on variables directly related to the probability distribution of the first fall frost date whereby the benefit of reaching maturity only a week or two later would be reflected in a simulation.

Estimates of such adaptation mechanisms can provide a transparent framework to assess the diverse effects of climate change on the agriculture. Preliminary results we exemplify below call for a fertile research agenda to estimate effects of individual climate change constraints. Such models hold promise for

bridging the gap between the econometric and agronomic modeling families by developing a common ground for analysis. Further, structural modeling in a theoretical framework where relationships are qualitatively understood at the outset can reduce omitted variable bias and potential misinterpretation of reduced-form counterparts. For example, reduced-form approaches can provide little basis for determining expected qualitative relationships. Structural approaches, on the other hand, can answer questions in terms of the estimated strength of qualitatively clear components necessary to facilitate welfare and policy analysis.

An Optimization-Based Model

Our conceptual framework of behavior is a constrained optimization model where the farmer determines a vector of choice variables or weather-dependent choice rules, $x(\cdot)$, including choice of crop mix and cultivars, other technology choices such as machinery and irrigation/drainage investments, planting dates, and factor input levels. The optimization problem for a risk-neutral farmer with opportunity cost π_0 is

$$(1) \qquad \max_{x(\cdot)\geq 0} \pi(x(\cdot), p, w, \theta) \equiv p(Q(\theta)).q(\theta, x(\theta)) - w(\theta)\cdot x(\theta) \text{s.t.} \pi \geq \pi_0$$

where p and w are output and input price vectors, Q and q are market and farmer output vectors, and the vector θ escribes the timing and level of the exogenous weather inputs.

Applying the envelope theorem to the profit function associated with (1) yields a decomposition of the long-run change in profit from a change in climate,

$$(2) \qquad \left.\frac{\partial \pi}{\partial \theta}\right|_{x=x^*} = \frac{\partial p}{\partial Q}\frac{\partial Q}{\partial \theta} q(\theta, x^*(\theta)) + \left(\frac{\partial q}{\partial \theta} + \frac{\partial q}{\partial x^*}\frac{\partial x^*}{\partial \theta}\right) p(Q(\theta)) - \left(\frac{\partial w}{\partial \theta} x^*(\theta) + w(\theta)\frac{\partial x^*}{\partial \theta}\right)$$

where x^* is the optimal decision vector. The first term represents the effect of output price on profit stemming from the large-scale effect of climate on aggregate supply given aggregate demand. This term is potentially significant if climate change affects production and product mix over broad areas. Grasping its magnitude requires estimating the correlation of heterogeneous regional climate change impacts and how they aggregate into global agricultural output and consequent local price impacts. This difficulty likely explains why climate change studies typically assume fixed prices (e.g. MNS, SHF, DG). However, this effect is likely to have attenuating implications because equilibrium price adjustments tend to spread economic effects across a broad array of markets and, thus, soften impacts on the most affected markets through product substitution.

The second term represents the contribution of climate change to profit through its effect on the individual farmer's output. Crop output can be expanded as the product of acreage $a(\theta)$ and yield $y(\theta, x(\theta))$ where

$$\frac{\partial q(\theta, x(\theta))}{\partial \theta} = \frac{\partial a(\theta)}{\partial \theta}\cdot y(\theta, x(\theta)) + \left(\frac{\partial y(\theta, x(\theta))}{\partial \theta} + \frac{\partial y(\theta, x(\theta))}{\partial x}\frac{\partial x(\theta)}{\partial \theta}\right)\cdot a(\theta)$$

and $a(\theta)$ is a subvector of $x(\theta)$. This expression highlights the importance of focusing carefully on the response of both the optimal crop mix and the yields of alternative crops to climate change, and how particular climate-dependent farmer responses affect each.

The third term in (2) measures the cost effect of climate change associated with climate-induced changes in input prices and input use. The former might stem from changing demand pressure on input markets. The latter arises from a wide range of possibilities for changing cultivation practices and crop mix. For example, a farmer might purchase more irrigation water on a given crop to compensate for reduced rainfall or adopt mitigating measures to maintain arable land in the event of an increase in farm-wide flooding, drought, or consequent adverse pest populations.

Such an optimization model thus provides a framework in which to analyze separate climate change impact mechanisms. Major adaptive behaviors within each channel can be explored separately to identify policy-relevant insights for improved adaptation. The model can obviously be expanded to consider additional mechanisms that affect adaptation subject to the limitations of econometric identification. For example, allowing risk aversion can facilitate welfare analysis of changing climate variability, in which case an

analysis of reservation utility can shed light on agricultural regions that might no longer farm, or other regions that might begin farming.

An Empirical Illustration

Obviously, an empirical illustration of specific modeling of each of the mechanisms delineated in this model is beyond the scope and space limitations of this paper. Alternatively, we present an empirical example that explores the yield impact channel, $\partial y(\theta, x(\theta))/\theta x \cdot \partial x(\theta)/\partial\theta$, to illustrate subtle but important potential for plausible adaptive behavior and opportunities that tend to remain unexplored in reduced-form models. In particular, we explore the potential effect on corn yield of a 5°F uniform warming through both extreme heat during different crop production stages and the widening of the frost-free period. We explore how the climate-dependent choice of planting date, represented by $\partial x(\theta)/\partial\theta$, may affect yield.

The example is fundamentally based on a statistical corn yield model with weather regressors matched to key stages of the corn production cycle, namely the vegetative, flowering, and the grain-filling periods (see Ortiz-Bobea 2011). This allows estimation of phenological regression coefficients that are disconnected from fixed calendar periods (Dixon et al. 1994). The advantage of this approach is that the regression results can be easily employed in simulations that allow for shifting growing seasons. Geographic variation in growing seasons can then be used to project future variation in growing seasons under climate change. The model specification is

$$y_{it} = \Sigma_s(\beta_{1,s}Prec_{its} + \beta_{2,s}Prec^2_{its} + \beta_{3,s}GDD_{its} + \beta_{4,s}\,DDD_{its}) + \Psi(t) + a_i + \epsilon_{it}$$

where y_{it} is yield in county i in year t; s is the set of key stages of corn production; *Prec*, *GDD* and *DDD* are precipitation, growing degree-days (8–32°C) and damaging degree-days (>34°C); $\Psi(t)$ is a quadratic time trend; and the a_i are county effects.

We use a county-level corn yield panel dataset (1985–2005) from a mostly rainfed area covering 8 states, which represents over 65 percent of US corn production. County production and state crop progress data were obtained from USDA-NASS and daily weather data for the 1950–2005 period is from Schlenker and Roberts (2009).

Following the literature, simulated impacts are obtained by multiplying estimated parameters by the projected mean climate change for the corresponding variables and time frame. However, the phenological approach allows shifting time frames for crop stages. In this context, climate differences are obtained by subtracting current mean climate for the current time frame of a crop stage from the projected mean climate for its simulated time frame. This contrasts with models based on monthly variables that keep the time frame, and therefore the growing season, fixed.

Results from the baseline corn yield model, assuming a fixed growing season (table 1), reflect estimated average damages of 26.3 percent for the sample. Of course, these damages have substantially heterogeneous geographic distribution, which raises significant issues of potential geographic adaptation of crop mixes, but we leave that analysis to another paper. Interestingly, over two-thirds of this damage is associated with high temperature during the flowering period, which is a short period in the full growing season (approximately 2-3 weeks in the June-August period, depending on location). This sharp sensitivity during the flowering period coincides with agronomic findings, but contrasts sharply with econometric models that use season-long weather variables.

The resulting optimization problem is represented in figure 1. The objective is to assess whether relaxation of the freezing constraints in the spring and fall provide

Table 1. Yield Sensitivity by Corn Growth Stage

Corn growth stage	Yield impact from a 5°F warming with a fixed growing season (%) / (bu/acre)	Share of stage influence in total yield impact (%)
Vegetative *(Planting to flowering)*	−8.9/−11.7	33.3
Flowering *(4 weeks around silking)*	−17.6/−23.0	65.8
Grain-filling *(Flowering to maturity)*	0.3/0.3	0.9
Full cycle	−26.3/−34.4	100

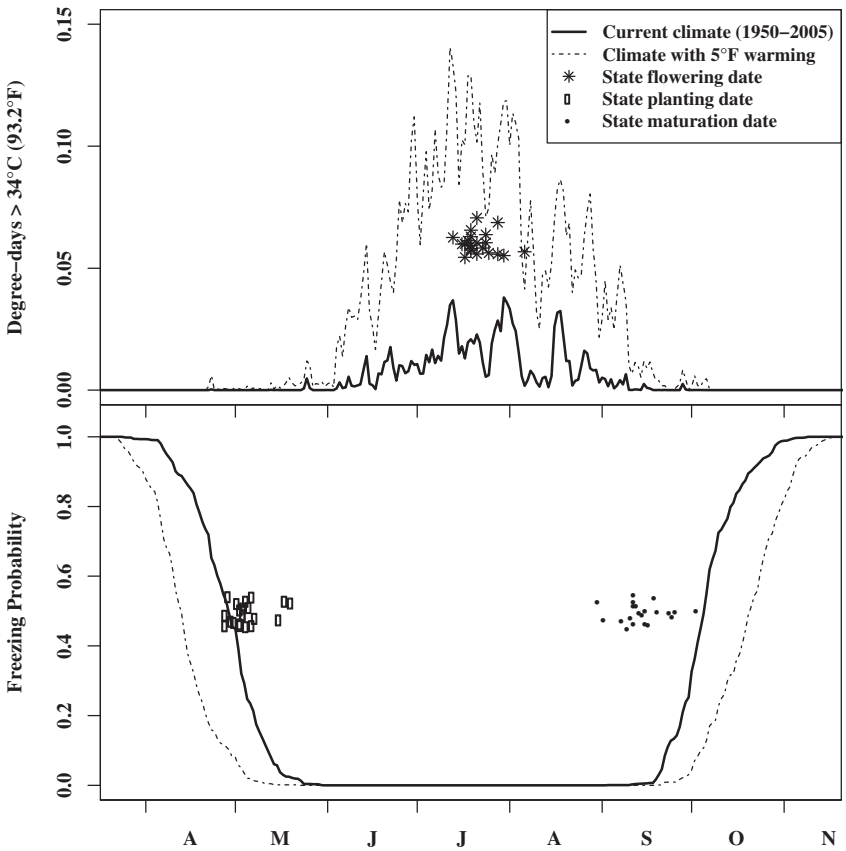

Figure 1. Key corn stages and climatic constraints in Iowa

sufficient flexibility of planting dates for farmers to reduce exposure to extreme heat during the sensitive flowering period.

If farmers in the Midwest are constrained by the length of the frost-free period, then we should expect a spatial pattern of earlier planting dates coupled with earlier frost-free days in the spring to emerge. This pattern is indeed verified in the first panel of figure 2. A similar pattern might also be expected in the fall, with later maturation dates associated with later first fall frosts if the fall frost date is constraining. The second panel of figure 2 shows this pattern up to a point (around day 290 of the year) after which there is a clear disconnect. Clearly, extending the frost-free period as depicted in the lower part of figure 2 shows that states with a narrower frost-free period tend to plant and reach maturity systematically at dates with higher probabilities of freezing. Only when the frost-free period reaches 180 days does the probability of frost at maturation decline to zero. These data suggest that the spring frost threshold is binding for all states, but the fall threshold is only binding for states with less than 180 frost-free days.

To explore the potential effect of shifting the growing season in the year by altering the planting date, we simulated earlier planting dates by shifting the planting date earlier in one-day increments until the planting date coincides with the new spring freezing threshold under a 5°F uniform warming. We also shifted the planting date later until the maturation date coincides with the new fall freezing threshold. At each increment, a new climate dataset was constructed for the time windows corresponding to the vegetative, flowering, and grain-filling periods. The spring and fall thresholds were set to maintain the current probability of freezing levels at planting and maturation for each state. This confines the simulation to a plausible range.

Simulation results are presented in figure 3 where each line represents an acreage-weighted state-level yield response to the shift in planting date. All states show considerable yield losses without planting adaptation as

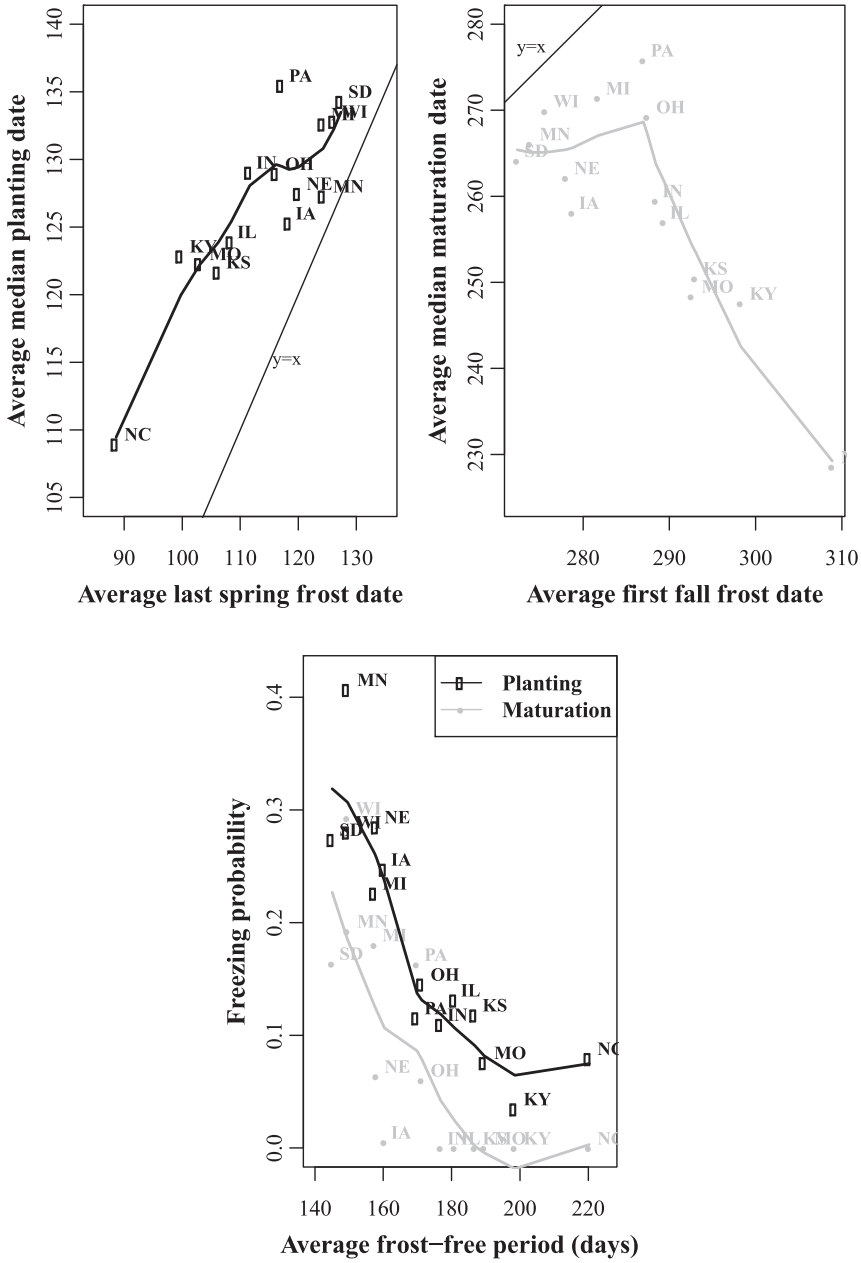

Figure 2. Corn growing season and freezing dates

shown by the negative intercepts. The downward sloping curves, however, show that earlier planting under a 5°F warming scenario reduces damages from higher temperatures. This is the result from shifting the most sensitive period of the production cycle away from higher temperatures in the summer months. Table 2 shows that earlier planting by around 2 weeks results in a significant reduction of damages, ranging from 30 to 70 percent depending on the state. In terms of value, this represents around $3.4 billion for the 8 states combined, or 14 percent of the region's $24 billion annual average production for the 2000–2010 period. For comparison, SHF estimate $5.0 billion in annual damages for the entire US agricultural sector with the same warming scenario together with an 8 percent increase in precipitation; DG estimate $1.3 billion in annual benefits for an alternative scenario.

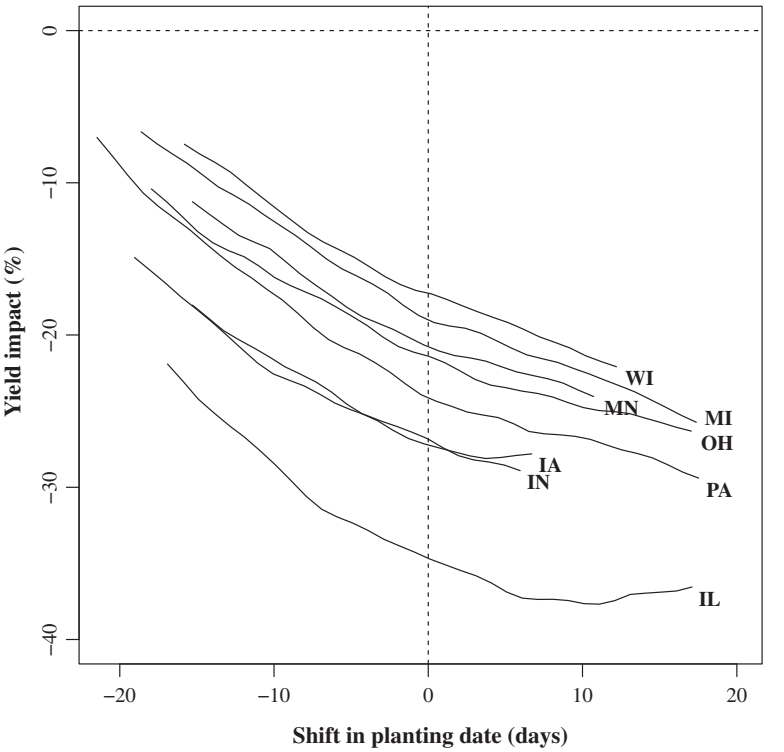

Figure 3. Overall state yield response and planting adaptation

Table 2. Corn Yield Impacts From a Uniform 5°F Warming

	Without change in planting date (%)/ (bu/acre)	With change in planting date (%)/ (bu/acre)	Impact mitigated with with adaptation (%)	Optimal change in planting date (days)	Savings from adaptation (Million 2010 US$)
Illinois	−34.7/−47.3	−21.9/−29.9	36.9	−16	$1,371
Indiana	−26.8/−35.3	−14.9/−19.6	44.4	−18	405
Iowa	−27.1/−37.2	−18.0/−24.7	33.6	−14	848
Michigan	−19.2/−21.6	−6.6/−7.5	65.3	−18	168
Minnesota	−20.6/−26.8	−11.2/−14.6	45.5	−14	330
Ohio	−21.4/−27.0	−10.4/−13.1	51.4	−17	116
Pennsylvania	−23.9/−24.7	−7.0/−7.2	70.6	−20	61
Wisconsin	−17.3/−20.8	−7.4/−8.9	56.8	−15	102
Full sample	−26.3/−34.4	−14.0/−18.5	44.1	−15.8	$3,401

Conclusion

In this paper we propose, and provide evidence on, the need for a model that elucidates some of the major mechanisms through which both the damaging effects and adaptation possibilities from climate change impact agriculture. We submit that a transparent structural econometric approach can open the door to more detailed adaptation policy analysis grounded in revealed preferences. A structural approach grounded in the science of crop production should also allow cross-checking the plausibility of overall reduced-form estimates. Our empirical example shows that plausible adaptation strategies with little extra cost could significantly reduce projected corn yield damages for the 8 states in the sample. The results are demonstrated by a yield model that introduces disaggregated phenological weather variables matched to the production cycle.

Several limitations of our proposed approach should be borne in mind. Crop progress data is available for major producing states only at the state level, obscuring some variations within states. Also, we have not considered other agronomic aspects, such as the accelerating effect of higher temperature on the crop cycle, the potential to adopt different cultivars, or the influence of lower solar radiation on crop photosynthesis during shorter spring days. Our model also assumes three distinct crop stages where weather inputs are separable.

The complexity of the effect of environmental conditions on yield typically leaves researchers with a choice between imperfect proxies. Some of these may imply strong restrictions on farmer flexibility, as our example shows. Weather variables that better capture the effect of environmental conditions and their interaction, such as water balance measures tied to relevant crop stages, also offer new tools for more transparent methods of econometric climate change assessment that may help bridge the gap between alternative methods used for assessing impacts. Indeed, better capturing of the effect of weather variables on production allows better assessment of the physical constraints farmers face but, more importantly, facilitates assessment of the possibilities available for adaptation that have received relatively less attention to date.

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