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Inter-annual Weather Variation and Crop Yields

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Abstract

While the effects of rising mean temperatures on agricultural output have been studied extensively, there is limited discussion of the impact of inter-annual weather variation on crop yields. This paper estimates the link between weather and crop yields separating the influence of (i) mean weather outcomes (i.e., climate) to which a farmer can adapt from (ii) unpredictable year-to-year weather fluctuations to which a farmer can only partially adapt as crops are planted before the weather shock is realized.

We find that corn in extreme climates, both hot and cold, are more sensitive to inter-annual weather variation than the ones in moderate climates. Global warming has two effects on corn yields: first, warming will induce farmers in moderate-temperate climates to plant varieties that are less robust to weather fluctuations, while farmers in cool climates will plant varieties that are more robust to weather fluctuations. Second, the elasticity of reductions in expected corn yields with respect to an increase in the standard deviation of weather fluctuations is -0.4. Since most farmers are eligible for subsidized crop insurance, an increase in weather variation also directly translates into added government payments.

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Agriculture is the sector of the economy most directly linked to weather, as precipitation and temperature directly enter the production function. Most of the existing literature that addresses the potential consequence of climate change focuses exclusively on the effects of a shift in mean weather outcomes (i.e., climate). This paper examines the influence of the second moment of the temperature distribution, i.e., year-to-year variance, on crop yields. The economic implications of mean shifts and changes in inter-annual variance are quiet distinct: farmers can adapt to shifts in mean weather outcomes by switching to various varieties of the same crop, by using various planting practices (e.g., sowing densities), or switching to a completely different crop. For example, corn varieties are often classified by the required degree days, i.e., the optimal sum of daily temperatures above a certain baseline.[1]

However, while mean weather (climate) is known, actual weather outcomes are random and unpredictable at the time of planting in spring. The time lag between the time of planting and weather realization is the crucial component that distinguishes a shift in mean weather outcomes from year-to-year variations. Once a farmer has committed to a certain crop by choosing a particular seed and planting practise, the weather outcome is realized and, in retrospect, it might have been better to grow a different variety or use a different planting practice.

Variation in weather hence has two dimensions: Average weather (or climate) varies in space, i.e., between different location. Year-to-year weather variation adds a time dimension, as weather outcomes at a given location vary between years. This paper utilizes a panel data set of corn yields to *simultaneously* estimate the outer envelope of corn yields attainable by adapting to various climates as well as the effect of inter-annual variation that reduce expected yields *below* the highest attainable one if the weather outcome would have been known in advance. The drop inside the outer envelope occurs because a suboptimal variety was grown for the particular weather outcome. The curvature or robustness of individual crop varieties determines how much weather fluctuations reduce observed yields below the outer envelope. If the curvature was zero or the plant was completely robust to inter-annual variations, one would remain on the outer envelope. However, if a crop is very sensitive, fluctuations will push observed yields within the outer envelope. We allow these additional productivity losses due to weather fluctuations to vary by crop variety. For example, corn species bread in the highlands of Peru show much more resistance to weather variation than the ones used in the Mediterranean. In the preferred model estimate below, the curvature of

[1]For a more elaborate discussion of degree days, see the data section below.

the outer envelope is a magnitude lower than the one of individual corn varieties, suggesting that year-to-year weather variations can have significant effects.

Another unique feature of our estimation strategy is that we allow for an endogenous choice of the planted crop variety which we index by the tangency point with the outer envelope. If the effect of inter-annual variation on crop losses is uniform for all varieties, farmers will choose a point of tangency that equals the average growing condition (climate). If, however, various crop varieties exhibit changing robustness to weather fluctuations, farmers might decide to grow a variety that has a lower yield at the mean weather outcome (climate) but suffers less productivity losses in response to weather fluctuations, hence giving a higher expected yield.

There are two channels through which climate change can alter the influence of inter-annual weather variation on expected crop yields: First, if the robustness of plant varieties to withstand varies between varieties, an increase in mean temperature might alter expected yields even if the inter-annual variance were to remain constant. This effect is due to the fact that farmers will adapt to a variety that might be more or less robust to these presumably constant fluctuations. Second, inter-annual variations might increase. If the relationship between weather and yields of an individual variety are concave, an increase in the variance of year-to-year fluctuations will unambiguously reduce expected yields by Jensen's inequality.

Several authors argue that an increase in extreme weather outcomes appears likely, yet it is very difficult to detect a statistically significant trend.[2] The large variability in weather outcomes makes it difficult to reject any Null hypothesis of an unaltered climate, yet the power of such test is also extremely low, i.e., one might be incapable of rejecting such a hypothesis in many circumstances even if the climate system were to change. Since one might only be able to detect such a trend after our climate is irreversible altered, it appears imperative to estimate the economic consequences of a potential increase in extreme weather outcomes. The relevance of this debate is manifested by the fact that almost all reinsurance companies by now have several climate scientists on staff to assess insurance risks under various climate scenarios. The market recognizes that these effects might potentially be large and significant and warrant further study. Moreover, there have been several episodes of extreme weather events in recent years. During the 2004 hurricane season, a record number of four hurricanes hit Florida, while a record number of ten cyclones hit Japan (Trenberth 2005). Similarly, a heat wave scorched Europe in 2003 and resulted in the

[2]For example, Trenberth (2005) argues that "although variability is large, trends associated with human interference are evident in the environment in which hurricanes form, and our physical understanding suggests that the intensity of rainfalls from hurricanes are probably increasing."

warmest August ever recorded in the northern hemisphere. Accordingly, vegetative gross primary productivity decreased by 30% (Ciais et al. 2005). Only 30 months later, the winter of 2005/2006 brought historic low temperatures to large parts of Eastern Europe and Russia suggesting that not only the mean temperature might be increasing, but also year-to-year variability.

The paper proceeds as follows: Section 1 presents a short model to highlight the decision problem of a farmer. The unique feature is the timing of the problem: a crop variety has to be chosen *before* yearly weather outcomes are realized. At the point when the decision is made, a farmer has only information about the distribution of weather outcomes, more specifically its mean and variance. Given this information, we derive an optimality condition for the variety a farmer should grow. Section 2 presents our data sources before the model is estimated in Section 3. The challenge is that the optimal variety, which is used in the square of the demeaned variable, is endogenous and a function of the parameters that need to be estimated. We hence jointly estimate the optimal variety and regression coefficients. The empirical results are used to identify the consequences of changes in the inter-annual weather variance in Section 4 before Section 5 concludes.

1 Model

Before we proceed with our model it might be helpful to contrast it with previous approaches in the literature. Cross-sectional studies have been designed to estimate the *outer envelope* of adaptation to mean growing conditions. For example Mendelsohn et al. (1994) use a reduced-form regression to explain farmland values as a function of climatic, socio-economic and soil variables. The idea behind such an approach is that in an efficient market farmland values will equal the discounted net present value of future profits, and hence capture the maximum attainable profit if the land was put to its best use. Since there is no time variation in climate for most of the last century, it is impossible to include a fixed effect for each location and the study relies purely on the cross-section. However, under specific error term assumptions, Timmins (2006) shows how use-specific error terms for forest, pasture, permanent and temporary crops can be recovered at a given location from the share of land devoted to each use. Lobell and Asner (2003) regress corn and soybean yield trends on temperature trends for counties with a negative correlation between yield and temperature anomalies and find the average impact between limited, but observable, climate change and yields for counties that would suffer under climate change.

Time series data of crop yields traditionally have been used to examine how *year-to-year weather fluctuations* influence yields, either for a specific location or by relying on a panel. Rosenzweig and Parry (1994) use calibrated crop-models that examine the effect of year-to-year weather fluctuations on crop yields to estimate the effect of changing climate conditions on yields and simulate farm adaptation. Deschenes and Greenstone (2004) use a panel data set to estimate the relation between profits and climatic variables. The authors regress profits in a county on climatic variables using county fixed effects.[3] Schlenker and Roberts (2006) link corn, soybeans, and cotton yields to weather outcomes over a 55 year period and find a highly significant nonlinear relationship. This second set of empirical studies do not capture farmer adaptations to various climates when identification comes from weather shocks that are random and unknown at the point of planting.

The idea behind this paper is to model both the effects of mean weather outcomes (climate) and year-to-year fluctuations simultaneously. For example, corn, one of the most prelevant crops world wide is grown in various climatic regions and various varieties have been bread to better adapt to local conditions. Assume there is a continuum of varieties that can be grown by a farmer. These varieties are indexed by γ_i, where γ_i is the point of tangency between the yield function of a particular variety and the outer envelope of all varieties. Log yields y_{it} in county i and year t are given as a function of the weather index x_{it}, other exogenous variables $\mathbf{z}_{it}$, and a county-fixed effect c_i, i.e.,

$$y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3(\gamma_i)[x_{it} - \gamma_i]^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

Yields in a particular year depend on the weather index x_{it} in two ways: The cross-sectional component specifies an outer envelope of the maximum attainable yield if the optimal variety is grown, i.e., $y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i$. The second component, $\beta_3(\gamma_i)[x_{it} - \gamma_i]^2$ measures additional productivity losses if weather x_{it} turns out to be different from γ_i, as shown in Figure 1. The additional yield loss $\beta_3(\gamma_i)[x_{it} - \gamma_i]^2$ is due to the time lag of the decision problem, where farmers first pick a variety γ_i (in spring), and nature than randomly draws a weather outcome x_{it} that might differ from γ_i. Hence, in hindsight, if the weather turns out to be warmer / cooler than expected, it might have been better to grow a different "warm-weather" or "cool-weather" variety instead.[4] Unfortunately, a farmer can only base

[3]It should be noted that fixed effects with a quadratic functional form in weather imply that profits are identified by the average weather variable, i.e., climate, as the demeaned squared variable is different from the square of the demeaned variable. This paper uses *both* the demeaned squared variable and the square of the demeaned variable.

[4]The empirical section below will use local regression techniques to check whether the assumed quadratic

his or her planting decisions on expectations about the weather, as the ultimate outcome is random. Note that the curvature of the additional crop loss $\beta_3(\gamma_i)$ can depend on the variety γ_i.

The outer envelope has an extremum at the level $\frac{\beta_1}{-2\beta_2} > 0$, and the above functional form combined with $\beta_1 > 0, \beta_2 < 0, \beta_3 < 0$ therefore implies that the first-order effect of temperature increases at the point of tangency are positive (negative) if γ_i is smaller (greater) than $\frac{\beta_1}{-2\beta_2}$ as displayed in the left graph of Figure 2. While it appears realistic to assume that farmers in cold climates appreciate warmer than-average weather outcomes, and vice versa, we would like to emphasize that our setup does *not* impose such a structure. If $\beta_1 = \beta_2 = 0, \beta_3 < 0$, any crop-specific constant would be picked up by the fixed effect c_i, and the first-order effect for a temperature increase at γ_i would be zero, i.e., the yield function of the specific variety would peak at γ_i as displayed in the right graph of Figure 2.

The above modeling framework hence superimposes two curves that have been estimated in the past. Cross-sectional hedonic studies have been specifically aimed at estimating the outer envelope $\bar{y}_i = \beta_1 \bar{x}_i + \beta_2 \bar{x}_i^2 + \bar{\mathbf{z}}_i \boldsymbol{\delta} + \epsilon_i$ (where $\bar{y}_i$ is the average log yield, $\bar{x}_i$ the average weather, or climate, over all x_{it}, and $\bar{\mathbf{z}}_i$ are average values of other outcomes within a county). Time series data of crop yields have traditionally been used to examine how year-to-year fluctuations in weather influence yields on a particular plot i, i.e., $y_t = c + \beta_1 x_t + \beta_2 x_t^2 + \mathbf{z}_t \boldsymbol{\delta} + \epsilon_t$. The purpose of this paper is to disentangles the outer-envelope of attainable corn yields from yield functions of individual corn varieties in a joint estimation. We hence present an application of two different forms of non-linearity in models with fixed effects: (i) changing marginal impacts that are a function of the absolute level of an exogenous variable, and (ii) changing marginal impacts that are a result from deviations from the group mean. Previous studies have sometimes mixed the two or used the former in the estimation, yet interpreted the results as if the they were estimated by the latter. A quadratic functional form combined with standard fixed effects implies that the marginal impact is still identified by the mean of the exogenous variable, i.e., in our case, climate. While fixed effects imply a joint demeaning of both the dependent and independent variables, the demeaned squared variable is *different* from the square of the demeaned variable, and we include both variables in our specification.

Before estimating our model, we need some theory as to which crop a farmers should grow. In the following we will derive the optimal solution given a continuum of crop varieties

functional form is consistent with real world observations. For example, one might wonder whether in hot climates, positive deviations from the mean climate produce larger reductions inside the outer envelope than negative deviations. The assumed symmetry as well as the other functional form assumptions appear to be in line with the data.

γ_i. Assume weather in county i is distributed with mean μ_i and standard deviation σ_i. Hence the expected yield as a function of the chosen variety γ_i is

$$\begin{aligned}\mathbb{E}[y_{it}] &= \mathbb{E}\left[\beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3(\gamma_i)[x_{it} - \gamma_i]^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}\right] \\ &= \beta_1 \mu_i + \beta_2\left[\mu_i^2 + \sigma_i^2\right] + \beta_3(\gamma_i)\left[\sigma_i^2 + [\mu_i - \gamma_i]^2\right] + \mathbb{E}\left[\mathbf{z}_{it}\right]\boldsymbol{\delta} + c_i\end{aligned}$$

The derivation is given in the appendix. Maximizing the expected yield with respect to the chosen variety γ_i we get the following first-order condition[5]

$$\frac{\partial \mathbb{E}[y_{it}]}{\partial \gamma_i} = \beta_3'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3(\gamma_i)[\mu_i - \gamma_i] = 0$$

First, note that if $\beta_3'(\gamma_i) = 0$, i.e., if the curvature on squared weather deviations does not depend on the variety, the solution is to choose variety $\gamma_i = \mu_i$. It would be best for a farmer to grow a variety that is tangent with the outer envelope of adaption possibilities at the average weather (climate) in the given county (Variety γ_i is indexed by their point of tangency with the outer envelope).

On the other hand if $\beta_3'(\gamma_i) \neq 0$, then there is no closed-form solution. However, we have the following equation that implicitly defines γ_i

$$\mu_i - \gamma_i = \frac{2\beta_3(\gamma_i) \pm \sqrt{4\beta_3(\gamma_i)^2 - 4\beta_3'(\gamma_i)^2\sigma_i^2}}{2\beta_3'(\gamma_i)} = \frac{\beta_3(\gamma_i)}{\beta_3'(\gamma_i)} \pm \sqrt{\left[\frac{\beta_3(\gamma_i)}{\beta_3'(\gamma_i)}\right]^2 - \sigma_i^2}$$

The deviation from the average climate $\mu_i - \gamma_i$ depends on how large $\frac{\beta_3(\gamma_i)}{\beta_3'(\gamma_i)}$ is compared to the variance of year-to-year weather fluctuations σ_i^2. Recall that $\beta_3'(\gamma_i)$ measures the change in how a variety can withstanding year-to-year fluctuations in weather, i.e., its robustness to random shocks. If crop varieties become more robust to random weather fluctuations, a risk-neutral farmer will decide to grow a variety that has a lower yield at the mean weather outcome (climate) but suffers less productivity losses in response to weather fluctuations, hence giving a higher expected yield. This behavior is illustrated in Figure 3. If all crop varieties exhibit the same robustness to squared weather deviations (i.e., the same curvature) as shown in the left panel, the largest expected yield will be obtained for the the variety that is tangent to the outer envelope at the mean weather variable. The right panel displays

[5]While farmers will maximize expected profits, corn is a fairly homogenous good with a uniform price, and hence maximizing expected profits is equivalent to maximizing expected yields as long as cost for seeds do not vary by variety. As will be shown below, the chosen γ_i is very close to μ_i, and as long as input cost vary smoothly with climate, they will not impact the choice of the optimal variety.

an example where the warmer-weather variety γ_2 (grey line) is more robust to weather fluctuations than the colder-weather variety γ_1 (black line). The former variety is more robust as the curvature is lower and can better withstand random weather shocks. For simplicity assume there is an equal probability that weather will turn out to be $\mu - x$ or $\mu + x$. At the mean weather outcome $\mu = \gamma_1$, the black line lies above the grey line, indicating that if the weather had no variability but would always equal the mean weather outcome, variety γ_1 would be preferable. However, given that the grey line has less curvature, the expected yield is higher for γ_2 under the equally likely weather outcomes $\mu - x$ and $\mu + x$.

So far we have talked about an appropriate weather index x_{it} and control variables $\mathbf{z}_{it}$ without defining them. In the following we will discuss the exact nature of each of these variables. Most crop varieties, especially corn, are classified by the number degree days they require to mature. Degree days are the sum of degrees between two bounds, where the lower bound for corn is usually set at 8°C, and the upper bound for corn was found to be 29°C (Schlenker and Roberts 2006).[6] The rational behind the concept of degree days is that plant growth is approximately linear in temperature between the two bounds. Farmers can adapt to various climates by growing different corn varieties that require more or less degree days to mature. We therefore chose the weather index x_{it} to be the sum of degree days between 8-29°C. The quadratic functional form $\beta_1 x_{it} + \beta_2 x_{it}^2$ allows for decreasing marginal value of additional degree days in this category.

While temperatures between 8-29°C are beneficial to plant growth, temperatures above 29°C quickly become harmful (Schlenker and Roberts 2006). The set of control variables $\mathbf{z}_{it}$ therefore include the square root of degree days above 29°C. The square root has a higher R-square than a linear specification. It is also preferable on theoretical grounds as it implies decreasing marginal damages that remain negative, while a positive quadratic term under a quadratic specification implies that additional degree days eventually become beneficial, which is at odds with empirical observations.[7] As a sensitivity check, the model is reestimatd using both a linear and quadratic specification and the results remain robust (See Table 4 and Table 5) in the empirical section below. One noteworthy fact is that these harmful effects appear consistent for northern and southern counties, suggesting that there is limited potential for adaptation. If adaptation possibilities were readily available, one would expect that southern counties should engage more in them as higher temperatures are

[6] A day of 5, 8, 10, 29, and 30 degrees Celsius would constitute 0, 0, 2, 21, and 21 degree days respectively.

[7] Note that there is an upper bound on the total number of degree days 8-29°C, but there is no upper bound on degree days above 29°C.

more frequently observed. Moreover, while average yields have increased almost threefold over the last 50 years, the critical value when temperatures become harmful has remained unchanged at 29°C. Since this critical value is robust across time and various climatic regions, it appears appropriate to include it in the set of control variables $\mathbf{z}_{it}$: In contrast to degree days 8-29°C, there appears limited adaptation potential. An increase in year-to-year variance might increase the expected occurrence of heat waves $\mathbb{E}[\mathbf{z}_{it}]$ and lower expected yields, but the distinction to x_{it} is that this loss is *not* impacted by the choice of the variety. Other control variables included in $\mathbf{z}_{it}$ are a quadratic functional form of precipitation, as well as year-fixed effects to account for the almost threefold increase in average yields over the last 55 years.

The data sources are outlined in more detail in the following section before we jointly estimate individual yield functions, the outer envelope, and the point of tangency γ_i in Section 3. Most of the time γ_i turns out to be close to μ_i. However, an inaccurate choice of γ_i will give inconsistent estimate for β_3, the parameter of interest.

2 Data

The dependent variable in our study are yearly county-level log corn yields as reported by the National Agricultural Statistics Service (NASS) for the years 1950-2004. The counties in our sample as well as the number of observations in each county are displayed in Figure 4. In this study we focus on corn, one of the crops with the largest planting area. In 2002, roughly 20% of total cropland in the United States was used to grow corn. Furthermore, corn is grown in various climatic regions both within the United States as shown in Figure 4 as well as internationally.

There is ample evidence that highly irrigated agriculture in the arid Western United States is fundamentally different from dryland agriculture in the Eastern United States (Schlenker et al. 2005). We therefore exclude all counties east of the 100 degree meridian, the traditional boundary between irrigated and dryland agriculture (Reisner 1986). The 100 degree meridian is included as a line in Figure 4. Since we are particularly interested in the effects of weather deviations from the mean outcome in a county, we only include counties that report yields in at least half of our 55 year period, i.e., that have at least 28 observations. Table 1 lists the descriptive statistics for the entire sample, as well as for all counties east of the 100 degree meridian, and the ones that have at least 28 observations. Our default data set of counties east of the 100 degree meridian with at least 28 observations is not only representative of the full data set, but also includes 86% of all observations. We present a sensitive analysis to various cutoff rules other than 28 in the empirical section below.

We match the yield data with yearly climatic variables derived from the PRISM grid, a fine-scale (2.5x2.5 mile grid) monthly weather history for the contiguous United States. The derivation of the climate variables is outlined in further detail in Schlenker and Roberts (2006). We link each grid of the "Parameter-elevation Regressions on Independent Slopes Model" (PRISM) to the surrounding NOAA weather stations with daily weather records to uncover the spatial smoothing procedure underlying PRISM. This smoothing procedure is then utilized to derive the daily temperature distribution at each grid cell between the minimum and maximum observed value. Finally, the climate variables are then averaged over the agricultural areas in all PRISM grids within a county obtained from Landsat satellite images. The distribution of temperatures within each day is used to derive the number of degree days between $8°C$ to $29°C$. Degree days are simply the number of degree above the lower threshold of 8°C up to a maximum of 21 for the upper bound of 29°C. Plant growth is approximately linearly increasing in temperature between 8°C and 29°C, i.e., plant growth under $12°C$ is approximately twice as large as under $10°C$.[8] The number of degree days are summed over all days in the growing season.[9] Table 1 also gives the average absolute deviation from a county's mean weather as a measure of year-to-year variability. A county with a constant climate in each year would have zero deviations from the mean. Increasing values imply increasing year-to-year variation. Finally, temperatures above 29°C become harmful and negatively influence plant growth, damaging the plant.

We choose a quadratic functional form for the beneficial degree days category 8-29°C. The presumption is that we will observe an inverted U-shape, where the negative quadratic term implies decreasing marginal impacts of additional degree days in this category. The coefficient on degree days above 29°C is expected to be negative to capture the harmful effects of heat waves. We choose the square root of harmful degree days above 29°C to account for decreasing marginal damages - once a plant is severely damaged, further heat episodes have limited negative impacts. Intuitively, a plant can only die once. The square root fits the data better than a linear functional form. The third climatic variable we include is total precipitation during the six-months period April-September as well its squared term. The presumption is that there is an interior maximum, as too much or too little precipitation

[8] The former constitutes 12°C - 8°C = 4 degree days, while the latter are only 10°C - 8°C = 2 degree days.

[9] We use the 6-months period April through September as planting dates vary between regions, but our results are insensitive the the chosen months.

is harmful for a plant. It should be noted that we use *log* yields as the dependent variable and hence our independent variables interact multiplicatively.

The functional from assumptions are compared to nonparametric local regression in the empirical section below where we find that assumed functional forms are consistent with the data and robust to various specification checks.

3 Empirical Results

In the following we will estimate the functional relationship between log yields y_{it} in county i at time t and the weather index x_{it}, which equals the number of degree days 8-29°C. As mentioned in the previous section, corn varieties are classified by the required number of degree days for the variety to mature. Hence farmers can adapt to various climates by choosing the appropriate corn variety. The outer envelope of adaption possibilities is given by $\beta_1 x_{it} + \beta_2 x_{it}^2$. Weather is random and unknown at the time of planting, and might differ from the optimal degree days requirements of a particular crop variety. Deviation from the optimal degree days requirement result in crop yields that lie within the outer envelope (as it would have been better to grow a different variety in retrospect) and are given by the term $\beta_3(\gamma_i)[x_{it} - \gamma_i]^2$, where γ_i is the optimal degree days requirement.

Other climatic variables included in the control variables $\mathbf{z}_{it}$ are precipitation (as well its squared term) and the square root of degree days above $29°C$, which capture the effects of harmful heat waves. The distinction between x_{it} and $\mathbf{z}_{it}$ is that a farmer can adapt to the former, while the negative impacts of the latter can not be influenced by choosing between various varieties. Other controls in $\mathbf{z}_{it}$ are year fixed effects to account for the almost threefold increase in average yields in our data set. The error terms ϵ_{it} are allowed to be spatially correlated within a year, but are assumed to be independent between years as weather is random. The estimation equation is

$$y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3(\gamma_i)[x_{it} - \gamma_i]^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

The challenge in the estimation is the endogeneity of the optimal variety γ_i. The optimal variety depends on how the curvature for year-to-year weather fluctuations β_3 changes in degree days 8-29°C. However, β_3 can only be estimated consistently if yearly weather outcomes x_{it} are demeaned by the correct point of tangency γ_i. Hence we need to estimate them jointly.

A simple example will motivate this point: β_3 measures the curvature of the yield function in excess of the constant curvature of the outer envelope. Recall the right panel of Figure 2 where the curvature of the outer envelope was zero, and all black solid lines peak at the mean climate. The term β_3 is the curvature of this black line, which was assumed to be largest for county 1, i.e., the slope changes rapidly for deviations from the mean. The curvature is lowest for county 2, which exhibits less rapid changes in the slope. In the left panel of Figure 2, this curvature is superimposed on top of the (constant) curvature of the outer envelope. In general, incorrectly assuming a constant curvature of β_3 in Figure 2 will imply that the curvature of the outer envelope might be inaccurately estimated as the variation in β_3 is picked up by outer envelope β_2. For example, if β_3 is increasing in γ_i, weather deviations in hot climates would be more harmful and push observed yields, and hence average yields, further inside the outer envelope than in cold climates. Inaccurately assuming a constant β_3 implies that the curvature of the outer envelope (β_2) is overestimated as it inaccurately reduces observed yields in hot climates, which in reality are lower due to a larger β_3. Similarly, demeaning by an inaccurate γ_i will give a biased estimate of β_3.

We hence allow for an endogenous choice of γ_i when we minimize the sum of squared residuals from the model. The exact description of the estimation strategy is given in the appendix. To allow for a flexible functional form of the $\beta_3(\gamma)$, we use a fifth-order Chebyshev polynomial.[10]

Results for the preferred model are given in the first column of Table 2. The outer envelope of degree days $8-29$°C peaks at 3029, while the maximum number of degree days for our 183 days growing period is 3843 degree days. Both the linear and quadratic terms are highly statistically significant, even after adjusting for the spatial correlation of the error terms. There are two approaches in the literature: Anselin and Florax (1995) impose a parametric structure of the spatial auto-correlation, which requires a weighting matrix that specifies how error terms are correlated up to a multiplicative constant, i.e., the spatial equivalent of a time-series AR(1) process. The potential problem of this approach is that the estimate of the variance-covariance matrix will be inconsistent if the weighting matrix is incorrectly specified. This problem is avoided in the second variant pioneered by Conley (1999) who instead relies on a non-parametric approach that does not require the specification of a weighting matrix, but might be less efficient. In this study we follow the latter as we have a set of counties that is not contiguous and a standard row-normalized contiguity-matrix becomes less appropriate.[11]

[10] We use different order Chebyshev polynomials but obtain similar results.

[11] The approach of Conley (1999) is an application of Newey and West (1987). Accordingly, we use a Barlett window in the longitude and latitude dimensions with a cutoff value of 5 degrees, or 350 miles. We

The coefficient on squared weather deviations from the point of tangency $(x_{it} - \gamma_i)^2$ is negative and highly significant. We use a m^{th}-order Chebyshev approximation with coefficients $\boldsymbol{\alpha} = [\alpha_1,\ \alpha_2,\ \ldots,\ \alpha_m]$ to approximate $\beta_3(\gamma_i) = \beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)\right]$, where $T_j()$ is the j^{th}-order Chebyshev polynomial. The reported coefficient on "degree days $8 - 29°C$ deviation squared" in Table 2 is the term β_3. The curvature is almost 20-fold the size of the curvature of the outer envelope, suggesting that yield curves of individual crop varieties lie strictly within the outer envelope and deviations from the tangency point can lead to significant additional reductions in yields.

Since the individual coefficients $\boldsymbol{\alpha}$ are difficult to interpret, we instead display the sum of the function $\beta_3(\gamma_i)$ and the constant $\beta_2 = -0.298$ in the top left panel of Figure 5. The term $\beta_2 + \beta_3(\gamma_i)$ measures the influence of inter-annual weather variation on expected crop yields. Strikingly, crop varieties in moderate temperate climates with degree days 8-29°C between 1750 and 2750 are the most robust varieties. Figure 5 shows that crop varieties found in either cool or hot climates are much less capable of withstandanding year-to-year fluctuations. Recall that we allow the point of tangency between individual yield curves and the outer envelope to be determined endogenously. Since the range of crop varieties show different degrees of robustness to inter-annual weather variation in Figure 5, it is indeed optimal to grow varieties that have a tangency point different from the average weather (climate) but are more robust. Deviations from the average weather (climate) range from -16.5 to +29.4 degree days $8 - 29°C$, with an average absolute deviation of 5.05. For comparison, the average within-county standard deviation of degree days $8 - 29°C$ for this subset of the data is 98.9.

The coefficient on the square root of degree days above 29°C is negative and highly significant, suggesting that there are large damaging effects from heat waves. Finally, the precipitation variable peaks at 24.8inches, which is close to predictions obtained in laboratory experiments.

Before presenting sensitivity checks for various subsets of the data, the functional form assumption of the preferred model can be cross-checked with the help of nonparametric local regressions. In each of the graphs of Figure 6, coefficient estimates from the first column in Table 2 are used to derive error terms while omitting one explanatory variable at a time.[12] The local regression of these error terms are then plotted against the exogenous variable that was omitted in the construction of the error terms. In case a functional form assumption

force the identification to come from contemporaneous correlation of the error terms in our panel data set.

[12] For example, in the top left graph, the error terms were constructed as $u_{it} = y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \mathbf{z}_{it}\boldsymbol{\delta} - c_i$, omitting the term $\beta_3(\gamma_i)[x_{it} - \gamma_i]^2$

was incorrect, the smoothed error terms from the local regression will exhibit a shape different from the one assumed in the model. For example, one might wonder whether positive deviations from county means are more harmful than negative deviations in warm climates, and vice versa in cold climates. However, the top four graphs of Figure 6 suggest that a quadratic (and hence symmetric) functional form assumption for deviations from the mean weather outcome in a county are appropriate for all four quartiles of counties sorted by mean weather. Similarly, the quadratic functional form for the outer envelope appear reasonable as shown in the bottom left graph.[13] Finally, the evidence whether a linear or square root is more appropriate to measure the harmful effects of heat above 29°C is mixed. While the harmful effects appear to be tapering off for higher levels, there is again very little probability mass in the upper end of the support. Since a large fraction of the predicted impacts under a changing climates in the next section rests on the frequency and extend of temperatures above 29°C, the sensitivity of these results to various functional form assumption for degree days above 29°C is checked as well.

Columns two to four in Table 2 uses various modelling checks. The corresponding within-curvature for each model is displayed in Figure 5. We will first discuss the results on the coefficient on weather deviations. Column (2) in Table 2 and the top right panel of Figure 5 exogenously forces the tangency point between inner and outer envelope to occur at the mean number of degree days 8-29°C in each county. A farmer has an incentive to grow a variety different from the mean weather outcome if the curvature is changing rapidly. Accordingly, it is predominantly farmers in cool or hot climates that choose crop varieties different from the mean weather outcome as the curvature is changing most rapidly for these subgroups. Exogenously fixing the tangency point at the mean weather variable leads to a misspecification for these counties and hence the curvature is estimated incorrectly for cold and hot varieties as shown in Figure 5. Column (3) in Table 2 and the bottom left panel of Figure 5 further restricts the within curvature $\beta_3(\gamma_i)$ to be constant among all crop varieties. This is unduely restrictive in light of the other panels in Figure 5. Note how the curvature of the outer envelope (β_2) is larger in column (3) than in column (1), because the former inaccurately assumes uniform damages of squared weather deviations and the larger damages in both hot and cool climates are partially picked up by the outer envelope. The change in coefficient, however, is limited.[14] Finally, column (4) in Table 2 and the bottom

[13]The one exception is for very hot climates, but there are very few observations in this range. The probability density function of the underlying observations is added in grey.

[14]Partly because the number of counties in both hot and cool climates is limited.

right panel of Figure 5 use quadratic yield trends by state instead of year fixed effects. If weather was highly spatially correlated, the impact of a weather shock in a particular year would be absorbed by the year dummy. Any identifications comes from weather deviations within a year. A quadratic yield trend by state avoids this problem. The main difference of yield trends is a tighter significance band for warm climates. This is not surprising as heat waves tend to be spatially correlated.

Other climatic variables remain fairly constant for various specifications in Table 2. The peak level of degree days 8-29°C changes from 3029 in the first column to 2971, 2973, and 2730 in the remaining three columns, respectively. Similarly, the optimal precipitation level moves very slightly from 24.8inches in the first column to 24.8, 24.8, and 24.1 inches in the remaining three columns. Degree days above $29°C$ hardly change at all and remain very significant. Only in the case of quadratic yield trends by state do they change slightly, which again might be explained by the fact that heat waves are spatially correlated and impact most counties in our sample in a given year, and hence part of the effect of heat waves is picked up by the year fixed effects in the first column.

Our results are also robust to what counties are included in the analysis. Table 3 gives the regression coefficients if the sample includes (1) counties east of the 100 degree meridian that report yields in all 55 years, (2) counties east of the 100 degree meridian that report yields in at least 14 out of the 55 years, (3) all counties east of the 100 degree meridian with corn yields, and (4) all counties in the United States with corn yields. Regression coefficients remain fairly robust. The peak level of degree days 8-29°C changes to 2656, 3001, 3013, and 2959, respectively, while optimal precipitation levels become 24.0, 24.9, 24.9, and 24.7 inches. The largest differences are that the subsample of counties with 55 records is limited to northern counties that are cooler, and the data set using all counties includes highly irrigated counties in the West. Irrigation makes weather deviations less harmful, which is shown in the bottom right graph of Figure 7 that displays the corresponding within-curvature on the squared weather deviations term.

One might wonder whether the effects of climate show up in the fixed effects as climate, the weather average, is fairly stable over the period of this study and hence there is no variation in climate for a given county over time. In this case one might observe fixed effects to vary systematically in the variable degree days $8 - 29°C$. The fixed effects are displayed in Figure 8, as well as a linear regression line linking the fixed effects to corresponding values in the average degree days $8 - 29°C$. While there is a small negative relationship, it could also be the result of cooler climates being correlated with better soils or other time-invariant variables that positively influence yields.

The next section will use the regression results to examine the effects of potential changes in the variance on expected corn yields.

4 Impacts

The regression results from the previous section can now be used to evaluate the potential impacts of a change in climatic conditions. We focus on the impact of inter-annual variance on corn yields, which, to our knowledge, have not been examined before. Year-to-year fluctuations enter expected yields in two distinct ways through the terms $[\beta_2 + \beta_3(\gamma_i)]\sigma_i^2 + \mathbb{E}[\mathbf{z}_{it}]$.

First, an increase in the variance σ_i^2 will lower expected yields as individual yield functions are concave functions, i.e., $[\beta_2 + \beta_3(\gamma_i)]$ is the sum of two negative terms. Furthermore, as outlined in Schlenker and Roberts (2006), heat above 29°C (84.2 degrees Fahrenheit) consistently becomes harmful for corn in various geographic regions, suggesting that extreme heat is uniformly harmful and there is limited adaptation potential. If adaptation possibilities were readily available, we would expect that warmer regions should be less sensitive to these high temperatures, as farmers have larger incentives to adapt to the more frequently observed high temperatures. An increase in the variance therefore also increases the sum of daily degrees above 29°C, and the square root of degree days 29°C is a control variable in $\mathbb{E}[\mathbf{z}_{it}]$.[15] Table 4 reports the decrease in yields attributable to the increased standard deviation σ_i. The distribution of impacts as a function of the current climate is displayed in Figure 9. One special feature might warrant further explanation: the combined impacts (which are in larger parts driven by the increased frequency of temperatures above 29°C) are not necessarily largest for warmer counties. This is partly due to the reason that counties with hotter temperatures have lower inter-annual variances in temperature to begin with. While increases in mean temperatures primarily impact agriculture in currently warm regions,

[15] The increased frequency in observed temperatures above 29°C is derived in the following way: We jointly estimate the variance-covariance matrix of minimum and maximum temperature deviations from daily temperature averages in a county for our 55 year data set. The variance-covariance matrix is allowed to vary by month but held constant within a month. We then increase each element of the variance-covariance matrix by the stipulated uniform increase in the standard deviation. Finally we simulate 1000 years by adding random draws from the variance-covariance matrix of minimum and maximum temperatures to the observed corresponding averages in the past for each day and derive the average number of degree days above 29°C during the growing season in each year.

increases in the variance would hit cool and moderate-temperate regions as well.

Table 4 reveals that the average elasticity of expected yields with respect to an increase in the standard deviation of year-to-year weather fluctuations is about -0.4, which is rather large. It should be noted that the larger share of these damages is attributable to an increased frequency of temperatures above 29°C. The concept of degree days 8-29°C assumes time separability as it simply sums the truncated temperatures between these bounds. Since a growing season includes approximately 120 days, randomness in daily outcomes gets averaged out as long as these randomness *stays within these bounds*. This explains why the resulting impact of degree days 8-29°C is outweighted by the impact of temperatures above 29°C. Since the frequency of these hot temperatures above 29°C is the largest driver behind the impacts, we check the sensitivity of the results to the functional form assumption for degree days above 29°C in Table 5. The local regression in the bottom right graph of Figure 6 suggests that other plausible specification could be linear or quadratic. Both are evaluated, with very limited effect on the overall results.

The combined effect of an increase in the standard deviation can be quiet substantial and would have large impacts on current crop insurance programs, which covered a total liability of 47 billion dollars in 2004. More than 75% of all acres planted were insured for both corn and soybeans in 2004, while the number exceed 90% of the planted area for cotton. Crop insurance premiums in the United States are not high enough to cover expected losses, and hence the government is currently subsidizing these programs. Total subsidies amounted to US$2.5billion in 2004. A potential increase in the variability would result in even larger indemnities, which, given current subsidized rates, would imply significant additional cost for the government.

There is a second indirect effect attributable to the inter-annual variance under climate change. If average temperatures were to change, farmers will grow different crop varieties which various robustness to inter-annual variation. Intuitively, regions that currently have cool climates will switch to *more robust* corn varieties with lower reductions caused by inter-annual variation in weather. On the other hand, regions that currently have moderate-temperate climates will switch to corn varieties that are *less robust* to weather variations. Table 6 reports changes in expected yields due to changing robustness of corn varieties to withstand year-to-year fluctuations under the Hadley III climate change scenario which will underlie the next report by the Intergovernmental Panel on Climate Change (IPCC).[16] In the medium term (2020-2049), impacts range from a 10% reduction in yields for moderate-

[16]We us the predicted changes in minimum and maximum temperature to derive changes in degree days.

temperate counties that become warmer and are forced to grow corn varieties which are less robust to year-to-year fluctuations in weather, to an increase in expected yields by 6% for cooler counties that become warmer and hence can grow corn varieties that are more robust to changes in weather variations. Average impacts are relatively small at approximately two tenth of a percent. For the period 2070-2099, impacts range between a 29% reduction in yields and a 7% increase. Average impacts vary between a small decline of 0.7% to a 6% decline, depending on the chosen climate change scenario.

5 Conclusions

We use a panel data set of corn yields to jointly estimate (i) the outer envelope of adaptation possibilities by switching to various corn varieties and cropping practises and (ii) additional reductions in expected yields due to unpredictable weather fluctuations between years. The latter effect arises from a timing problem, where farmers have to commit to a corn variety in spring when actual weather outcomes for the main growing season (summer) are random and unknown.

Crop varieties in cool and warm climates, which are already stressed, exhibit more sensitivity to weather fluctuations. Farmers hence have an incentive to grow a variety whose yield lies strictly inside the outer envelope of possible adaption strategies at average weather (climate), but which is more robust. Omitting this endogenous crop choice biases the results for cool and warm climates where the robustness of plants changes most rapidly and hence the incentive to grow a variety with a tangency point at the outer envelope that is different from the mean weather outcome is largest.

We next examine the implications of inter-annual weather variation on corn yields under global warming and separate two effects: First, there is an increase (decrease) in expected yields for currently cool-temperate (moderate-temperate) counties as warming implies that farmers will switch to corn varieties that are more (less) robust to weather fluctuations, even holding weather variation *constant*. Second, we calculate the effects of increased year-to-year fluctuations on expected corn yields, attributable to the concavity of the yield function of individual corn varieties as well as the increased likelihood of crossing the 29°C threshold where temperatures become harmful. The effect due to concavity of the yield function are lower than the ones attributable to an increased frequency of temperatures above 29°C. These results are in line with the concept of degree days, which assumes time separability in temperatures between 8 and 29°C. Increasing daily fluctuations while leaving the mean unchanged has limited effects as long as temperatures do not cross these bounds. However, if an increase in the variance results in more frequent or larger crossing of the upper threshold at 29°C, expected yields might be significantly reduced. The elasticity of expected corn yields with respect to an increase in the standard deviation of weather fluctuations is approximately -0.4.

The increased exposure to weather variations would have to be reflected in crop insurance premiums. Currently, premiums are not high enough to cover liabilities, and premium subsidies totaled 2.5 billion in 2004. The total liability of the crop insurance program amounted to 47 billion. An across the board reduction in yields of 10% due to increased variability would require additional subsidies of 3.3 billion at a coverage rate of 70%, assuming the premium structure is not adjusted.

Finally, there are several caveats to our analysis. First, it relies on a panel data set of *past* corn yields, and hence will not be able to pick up technological innovations in corn varieties (e.g., varieties that are more robust to weather fluctuations), or the effects of CO_2 fertilization. However, while average corn yields have gone up almost threefold in our 55 year sample period, the harmful upper threshold has remained unchanged, suggesting there is limited potential to adaptation and the effects of CO_2 fertilization are still debated (Long et al. 2005). Second, since we limit the data to corn yields, we do not capture adaptation possibilities by switching to other crops. Yet, corn is currently grown in various climatic regions all over the world.

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6 Appendix

6.1 Derivation of expected yield

The expected yield in county i becomes

$$\begin{aligned}\mathbb{E}[y_{it}] &= \mathbb{E}\left[\beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3(\gamma_i)[x_{it} - \gamma_i]^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}\right] \\ &= \beta_1 \mathbb{E}\left[x_{it}\right] + \beta_2 \mathbb{E}\left[x_{it}^2\right] + \beta_3(\gamma_i)\mathbb{E}\left[[x_{it} - \gamma_i]^2\right] + \mathbb{E}\left[\mathbf{z}_{it}\right]\boldsymbol{\delta} + c_i\end{aligned}$$

Define $\mathbb{E}\left[x_{it}\right] = \mu_i$ and $\mathbb{E}\left[[x_{it} - \mu_i]^2\right] = \sigma_i^2$, and we get using $\mathbb{E}\left[x_{it}^2\right] = \sigma_i^2 + \left[\mathbb{E}\left[x_{it}\right]\right]^2 = \sigma_i^2 + \mu_i^2$

$$\begin{aligned}\mathbb{E}[y_{it}] &= \beta_1 \mu + \beta_2\left[\mu_i^2 + \sigma_i^2\right] + \beta_3(\gamma_i)\mathbb{E}\left[[x_{it} - \mu_i + \mu_i - \gamma_i]^2\right] + \mathbb{E}\left[\mathbf{z}_{it}\right]\boldsymbol{\delta} + c_i \\ &= \beta_1 \mu + \beta_2\left[\mu_i^2 + \sigma_i^2\right] + \mathbb{E}\left[\mathbf{z}_{it}\right]\boldsymbol{\delta} + c_i \\ &\quad + \beta_3(\gamma_i)[\underbrace{\mathbb{E}\left[[x_{it} - \mu]^2\right]}_{\sigma_i^2} + \underbrace{\mathbb{E}\left[[x_{it} - \mu_i][\mu_i - \gamma_i]\right]}_{0} + \underbrace{\mathbb{E}\left[[\mu_i - \gamma_i]^2\right]}_{[\mu_i - \gamma_i]^2}] \\ &= \beta_1 \mu_i + \beta_2\left[\mu_i^2 + \sigma_i^2\right] + \beta_3(\gamma_i)\left[\sigma_i^2 + [\mu_i - \gamma_i]^2\right] + \mathbb{E}\left[\mathbf{z}_{it}\right]\boldsymbol{\delta} + c_i\end{aligned}$$

The first-order condition for the optimal variety γ_i hence is

$$\frac{\partial \mathbb{E}[y_{it}]}{\partial \gamma_i} = \beta_3'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3(\gamma_i)[\mu_i - \gamma_i] = 0$$

In the numerical implementation we look for the minimum of the following function for each of the counties i (groups) in our data set[17]

$$f(\gamma_i) = \left[\beta_3'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3(\gamma_i)[\mu_i - \gamma_i]\right]^2$$

with the following gradient and second derivative

$$\begin{aligned}f'(\gamma_i) &= 2\left[\beta_3'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3(\gamma_i)[\mu_i - \gamma_i]\right]\left[\beta_3''(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 4\beta_3'(\gamma_i)[\mu_i - \gamma_i] + 2\beta_3(\gamma_i)\right] \\ f''(\gamma_i) &= 2\left[\beta_3''(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 4\beta_3'(\gamma_i)[\mu_i - \gamma_i] + 2\beta_3(\gamma_i)\right]^2 \\ &\quad + 2\left[\beta_3'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3(\gamma_i)[\mu_i - \gamma_i]\right]\left[\beta_3'''(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 6\beta_3''(\gamma_i)[\mu_i - \gamma_i] + 6\beta_3'(\gamma_i)\right]\end{aligned}$$

[17] Using MATLAB's routine fminunc.

6.2 Estimation procedure

Using a m^{th}-order Chebyshev approximation with coefficients $\boldsymbol{\alpha} = [\alpha_1,\ \alpha_2,\ \ldots,\ \alpha_m]$ and $\beta_3(\gamma_i) = \beta_3\left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)\right]$ the model becomes

$$y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \underbrace{\beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\boldsymbol{\alpha}))\right]}_{\beta_3(\gamma_i)} [x_{it} - \gamma_i(\boldsymbol{\alpha})]^2 + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

Accordingly, the first-order condition of choosing the best crop-variety γ_i is

$$\frac{\partial \mathbb{E}[y_{it}]}{\partial \gamma_i} = \beta_3 \left[\sum_{j=1}^{m} \alpha_j T_j'(\gamma_i)\right] \left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)\right] [\mu_i - \gamma_i] = 0$$

6.2.1 Endogenous choice of crop variety

Total differentiation gives

$$\begin{aligned} 0 \;=\;& \left\{\beta_3 \left[\sum_{j=1}^{m} \alpha_j T_j''(\gamma_i)\right] \left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 4\beta_3[\mu_i - \gamma_i] \left[\sum_{j=1}^{m} \alpha_j T_j'(\gamma_i)\right] + 2\beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)\right]\right\} d\gamma_i \\ +\;& \left\{\beta_3 T_k'(\gamma_i) \left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right] - 2\beta_3 T_k(\gamma_i)[\mu_i - \gamma_i]\right\} d\alpha_k \end{aligned}$$

And hence

$$\frac{d\gamma_i}{d\alpha_k} = \frac{2T_k(\gamma_i)[\mu_i - \gamma_i] - T_k'(\gamma_i)\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right]}{\left[[\mu_i - \gamma_i]^2 + \sigma_i^2\right]\left[\sum_{j=1}^{m} \alpha_j T_j''(\gamma_i)\right] - 4[\mu_i - \gamma_i]\left[\sum_{j=1}^{m} \alpha_j T_j'(\gamma_i)\right] + 2\left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)\right]}$$

We will use this relationship in the nonlinear least squares procedure. The sum of squared residuals over counties $i = 1 \ldots N$ and time periods $t = 1 \ldots T$ as a function of the parameters $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}$ is

$$S = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\boldsymbol{\alpha}))\right] [x_{it} - \gamma_i(\boldsymbol{\alpha})]^2 - \mathbf{z}_{it}\boldsymbol{\delta} - c_i\right]^2$$

Using the following abbreviations:

$$e_{it} = \left[y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\boldsymbol{\alpha}))\right] [x_{it} - \gamma_i(\boldsymbol{\alpha})]^2 - \mathbf{z}_{it}\boldsymbol{\delta} - c_i\right]$$

$$\mathbf{x}_1 = \begin{bmatrix} x_{11} \\ x_{12} \\ \vdots \\ x_{1T} \\ x_{21} \\ \vdots \\ x_{NT} \end{bmatrix} \qquad \mathbf{x}_2 = \begin{bmatrix} x_{11}^2 \\ x_{12}^2 \\ \vdots \\ x_{1T}^2 \\ x_{21}^2 \\ \vdots \\ x_{NT}^2 \end{bmatrix} \qquad \mathbf{x}_3 = \begin{bmatrix} \left[1 + \sum_{j=1}^m \alpha_j T_j(\gamma_1(\boldsymbol{\alpha}))\right] [x_{11} - \gamma_1(\boldsymbol{\alpha})]^2 \\ \left[1 + \sum_{j=1}^m \alpha_j T_j(\gamma_1(\boldsymbol{\alpha}))\right] [x_{12} - \gamma_1(\boldsymbol{\alpha})]^2 \\ \vdots \\ \left[1 + \sum_{j=1}^m \alpha_j T_j(\gamma_1(\boldsymbol{\alpha}))\right] [x_{1T} - \gamma_1(\boldsymbol{\alpha})]^2 \\ \left[1 + \sum_{j=1}^m \alpha_j T_j(\gamma_2(\boldsymbol{\alpha}))\right] [x_{21} - \gamma_2(\boldsymbol{\alpha})]^2 \\ \vdots \\ \left[1 + \sum_{j=1}^m \alpha_j T_j(\gamma_N(\boldsymbol{\alpha}))\right] [x_{NT} - \gamma_N(\boldsymbol{\alpha})]^2 \end{bmatrix}$$

The partial derivatives become (where $z_{it}^{(k)}$ is the k-th column of $\mathbf{z}$)

$$\begin{aligned}
\frac{\partial S}{\partial \beta_1} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} x_{it} = -2\mathbf{e}'\mathbf{x}_1 \\
\frac{\partial S}{\partial \beta_2} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} x_{it}^2 = -2\mathbf{e}'\mathbf{x}_2 \\
\frac{\partial S}{\partial \beta_3} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\boldsymbol{\alpha}))\right] [x_{it} - \gamma_i(\boldsymbol{\alpha})]^2 = -2\mathbf{e}'\mathbf{x}_3 \\
\frac{\partial S}{\partial \alpha_k} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} \beta_3 \left[\left[T_k(\gamma_i(\boldsymbol{\alpha})) + \sum_{j=1}^{m} \alpha_j T_j'(\gamma_i(\boldsymbol{\alpha})) \frac{d\gamma_i}{d\alpha_k}\right] [x_{it} - \gamma_i(\boldsymbol{\alpha})]^2 - 2 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\boldsymbol{\alpha}))\right] [x_{it} - \gamma_i(\boldsymbol{\alpha})] \frac{d\gamma_i}{d\alpha_k}\right] \\
\frac{\partial S}{\partial \delta_k} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} z_{it}^{(k)} = -2\mathbf{e}'\mathbf{z}_k
\end{aligned}$$

We use the function `fminunc` in MATLAB to jointly solve for optimal variety γ_i as well as parameters $\boldsymbol{\alpha}, \boldsymbol{\beta}$, and $\boldsymbol{\delta}$ that minimize the sum of squared residuals while providing the gradient.

6.2.2 Fixed crop variety

In a sensitivity check the point of tangency is exogenously set to equal the average outcome in a county, i.e., $\gamma_i = \mu_i$. In this case the problem simplifies to

$$S = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \beta_3 \left[1 + \sum_{j=1}^{m} \alpha_j T_j(\mu_i)\right] [x_{it} - \mu_i]^2 - \mathbf{z}_{it}\boldsymbol{\delta} - c_i\right]^2$$

The partial derivatives become (where $z_{it}^{(k)}$ is the k-th column of $\mathbf{z}$)

$$\begin{aligned}
\frac{\partial S}{\partial \beta_1} &= -2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}x_{it} = -2\mathbf{e}'\mathbf{x}_1 \\
\frac{\partial S}{\partial \beta_2} &= -2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}x_{it}^2 = -2\mathbf{e}'\mathbf{x}_2 \\
\frac{\partial S}{\partial \beta_3} &= -2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}\left[1+\sum_{j=1}^{m}\alpha_j T_j(\mu_i)\right][x_{it}-\mu_i]^2 = -2\mathbf{e}'\mathbf{x}_3 \\
\frac{\partial S}{\partial \alpha_k} &= -2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}\beta_3 T_k(\mu_i)\,[x_{it}-\mu_i]^2 \\
\frac{\partial S}{\partial \delta_k} &= -2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}z_{it}^{(k)} = -2\mathbf{e}'\mathbf{z}_k
\end{aligned}$$

And the following Hessian (where $x_{ij}^{(k)}$ is the $[[i-1]T+j]^{th}$ element of $\mathbf{x}_k$)

$$\begin{aligned}
\frac{\partial^2 S}{\partial \beta_j \beta_k} &= 2\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}^{(j)}x_{it}^{(k)} = 2\mathbf{x}_j'\mathbf{x}_k && j,k=1,2,3 \\
\frac{\partial^2 S}{\partial \beta_j \delta_k} &= 2\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}^{(j)}x_{it}^{(k)} = 2\mathbf{x}_j'\mathbf{z}_k && j=1,2,3; k=1...N_z \\
\frac{\partial^2 S}{\partial \beta_j \alpha_k} &= 2\beta_3\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}^{(j)}T_k(\mu_i)\,[x_{it}-\mu_i]^2 && j=1,2; k=1...m \\
\frac{\partial^2 S}{\partial \beta_3 \alpha_k} &= 2\beta_3\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}^{(3)}T_k(\mu_i)\,[x_{it}-\mu_i]^2 - 2\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}T_k(\mu_i)\,[x_{it}-\mu_i]^2 && k=1...m \\
\frac{\partial^2 S}{\partial \delta_j \delta_k} &= 2\sum_{i=1}^{N}\sum_{t=1}^{T} z_{it}^{(j)}z_{it}^{(k)} = 2\mathbf{z}_j'\mathbf{z}_k && j,k=1...N_z \\
\frac{\partial^2 S}{\partial \delta_j \alpha_k} &= 2\beta_3\sum_{i=1}^{N}\sum_{t=1}^{T} z_{it}^{(k)}T_k(\mu_i)\,[x_{it}-\mu_i]^2 && j=1...N_z; k=1...m \\
\frac{\partial^2 S}{\partial \alpha_j \alpha_k} &= 2\beta_3^2\sum_{i=1}^{N}\sum_{t=1}^{T} T_j(\mu_i)T_k(\mu_i)\,[x_{it}-\mu_i]^4 && j,k=1...m
\end{aligned}$$

Table 1: Descriptive Statistics

Variable	Mean	Min	Max	σ	σ_{within}
All Counties					
Log Yield	4.20	-3.19	5.51	0.56	0.41
Degree Days 8-29°C (thousand)	2.17	0.78	3.45	0.46	0.10
Degree Days 8-29°C Deviation from Mean	81.65	0.00	464.45	61.75	56.50
Square Root Degree Days above 29°C	6.97	0.00	27.09	3.51	1.48
Precipitation (cm)	55.59	0.00	159.24	18.40	11.48
Number of observations	119091				
Number of counties	2791				
Counties East of the 100 Degree Meridian					
Log Yield	4.18	-3.19	5.32	0.54	0.40
Degree Days 8-29°C (thousand)	2.21	0.91	3.45	0.45	0.10
Degree Days 8-29°C Deviation from Mean	81.53	0.00	464.45	61.64	55.96
Square root Degree Days above 29°C	6.85	0.00	22.85	3.48	1.51
Precipitation (cm)	59.41	12.06	159.24	15.24	12.26
Number of observations	105591				
Number of counties	2325				
Counties East of the 100 Degree Meridian With at Least 28 Observations					
Log Yield	4.20	-3.19	5.32	0.53	0.40
Degree Days 8-29°C (thousand)	2.20	0.96	3.45	0.45	0.10
Degree Days 8-29°C Deviation from Mean	81.78	0.00	464.45	61.85	57.30
Square Root Degree Days above 29°C	6.75	0.00	22.85	3.40	1.50
Precipitation (cm)	59.31	12.86	159.24	15.06	12.16
Number of observations	102029				
Number of counties	2092				

Notes: The first four columns give the mean, minimum, maximum, and standard deviation of each variable in the years 1950-2004. The fifth column gives the average *within-county* year-to-year standard deviation.

Table 2: Log Corn Yields as a Function of Climate and Year-to-Year Weather Fluctuations

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Degree Days 8-29°C	1.81	1.93	1.92	2.02
	(7.99)	(8.37)	(8.42)	(8.61)
Degree Days 8-29°C Squared	-0.298	-0.325	-0.324	-0.370
	(5.46)	(5.79)	(5.83)	(6.58)
Degree Days 8-29°C Deviation Squared	-5.22	-6.82	-2.46	-6.92
	(5.46)	(4.32)	(5.67)	(6.70)
Degree Days 29°C	-9.68E-02	-9.69E-02	-9.69E-02	-9.91E-02
	(17.73)	(17.75)	(17.90)	(22.06)
Precipitation	1.01E-02	1.02E-02	1.02E-02	1.08E-02
	(6.79)	(6.87)	(6.81)	(7.22)
Precipitation Squared	-8.06E-05	-8.11E-05	-8.06E-05	-8.81E-05
	(7.47)	(7.55)	(7.52)	(7.91)
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	No
Yield trend by state	No	No	No	Yes
Number of observations	102029	102029	102029	102029
Number of counties	2092	2092	2092	2092
Minimum observations per county	28	28	28	28

Notes: Table lists coefficient estimates with t-values in brackets. Standard errors are adjusted for spatial correlation following Conley (1999). The first column presents results from the preferred model where the point of tangency between individual yield curves with *heterogenous* curvature $\beta_3(\gamma_i)$ and the outer envelope are endogenous. The second column forces the point of tangency to occur at the average weather (climate). The third column forces the curvature $\beta_3(\gamma_i)$ to be constant for all crop varieties. Finally, the fourth column uses the same setup as column 1 but relies on quadratic yield trends by state instead of year-fixed effects. The reported coefficient on "degree days $8-29°C$ deviation squared" is the term on weather deviations $(x_{it}-\gamma_i)^2$. In columns 1, 2, and 4 we report the value β_3 from the m^{th}-order Chebyshev approximation $\beta_3(\gamma_i)=\beta_3\left[1+\sum_{j=1}^{m}\alpha_j T_j(\gamma_i)\right]$, where $T_j()$ is the j^{th}-order Chebyshev polynomial. The function $\beta_3(\gamma_i)$ is displayed in Figure 5.

Table 3: Specification Checks: Log Corn Yields as a Function of Climatic Variables for Different Subsets of the Data

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Degree Days 8-29°C	2.58	1.81	1.79	1.78
	(9.55)	(8.26)	(8.23)	(9.43)
Degree Days 8-29°C Squared	-0.485	-0.301	-0.298	-0.301
	(7.20)	(5.71)	(5.67)	(6.50)
Degree Days 8-29°C Deviation Squared	-3.80	-4.85	-4.64	-3.27
	(5.73)	(5.40)	(5.38)	(5.14)
Degree Days 29°C	-1.07E-01	-9.57E-02	-9.57E-02	-8.98E-02
	(16.50)	(17.65)	(17.72)	(18.20)
Precipitation	1.47E-02	1.02E-02	1.00E-02	8.72E-03
	(7.97)	(7.02)	(6.96)	(6.85)
Precipitation Squared	-1.21E-04	-8.08E-05	-7.95E-05	-6.93E-05
	(8.66)	(7.75)	(7.70)	(7.52)
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	52800	105177	105591	119091
Number of counties	960	2241	2325	2791
Minimum observations per county	55	14	1	1

Notes: Table lists coefficient estimates with t-values in brackets. Standard errors are adjusted for spatial correlation using Conley (1999). The four columns use different subsets of the data. Model (1), (2), and (3) include all counties east of the 100 degree meridian with at least 55, 14, and 1 reported corn yields for the 55-year period 1950-2004. Model (4) uses all counties, including the ones west of the 100 degree meridian that mainly rely on irrigation.

Table 4: Changes in Expected Corn Yields Due to a Potential Increase in Weather Variation (Percent)

Variable	Mean	Min	Max	σ	Losers
Increase in Standard Deviation By 10 Percent					
Variance Degree Days 8-29°C	-0.62	-2.12	-0.16	0.25	1873
Sum Degree Days 29°C	-3.82	-5.70	-1.12	0.99	2092
Combined Impact	-4.41	-6.83	-1.36	1.14	2092
Increase in Standard Deviation By 25 Percent					
Variance Degree Days 8-29°C	-1.64	-5.58	-0.42	0.67	1873
Sum Degree Days 29°C	-9.45	-12.88	-3.25	2.26	2092
Combined Impact	-10.93	-16.93	-3.87	2.65	2092
Increase in Standard Deviation By 50 Percent					
Variance Degree Days 8-29°C	-3.61	-11.98	-0.94	1.45	1867
Sum Degree Days 29°C	-18.49	-24.19	-7.02	4.02	2092
Combined Impact	-21.40	-32.21	-8.18	4.73	2092
Increase in Standard Deviation By 100 Percent					
Variance Degree Days 8-29°C	-8.41	-26.39	-2.23	3.28	1858
Sum Degree Days 29°C	-34.67	-42.76	-15.21	6.30	2092
Combined Impact	-40.03	-57.01	-17.69	7.42	2092

Notes: Table lists the percentage impact on expected crop yields for various increases in the standard deviation of minimum and maximum temperatures while holding mean temperatures constant. Increases in the standard deviation have two effects: Increasing fluctuations in the sum of degree days 8-29°C, as well as an increased frequency of harmful degree days above 29°C. The table uses the regression results of the preferred model in the first column of Table 2. The first four columns give the mean, minimum, maximum, and standard deviation of the predicted impacts for the 2092 counties, while the last column gives the number of counties with statistically significant reductions at the 95% level after adjusting for spatial correlation.

Table 5: Sensitivity Check of Changes in Expected Corn Yields Due to a Potential Increase in Weather Variation (Percent)

Variable	Mean	Min	Max	σ	Losers
LINEAR SPECIFICATION IN DEGREE DAYS ABOVE 29°C					
Increase in Standard Deviation By 10 Percent					
Variance Degree Days 8-29°C	-0.52	-1.86	0.05	0.26	2048
Sum Degree Days 29°C	-2.79	-5.71	-0.22	0.83	2092
Combined Impact	-3.29	-6.30	-0.77	0.87	2092
Increase in Standard Deviation By 25 Percent					
Variance Degree Days 8-29°C	-1.38	-4.90	0.13	0.69	2048
Sum Degree Days 29°C	-7.30	-13.70	-0.74	2.00	2092
Combined Impact	-8.58	-15.15	-2.20	2.11	2092
Increase in Standard Deviation By 50 Percent					
Variance Degree Days 8-29°C	-3.04	-10.57	0.29	1.50	2048
Sum Degree Days 29°C	-15.56	-26.53	-2.40	3.79	2092
Combined Impact	-18.12	-29.21	-5.57	4.00	2092
Increase in Standard Deviation By 100 Percent					
Variance Degree Days 8-29°C	-7.10	-23.52	0.69	3.43	2048
Sum Degree Days 29°C	-33.50	-50.42	-8.41	6.42	2092
Combined Impact	-38.18	-54.65	-15.39	6.75	2092
QUADRATIC SPECIFICATION IN DEGREE DAYS ABOVE 29°C					
Increase in Standard Deviation By 10 Percent					
Variance Degree Days 8-29°C	-0.54	-2.46	-0.16	0.26	1826
Sum Degree Days 29°C	-3.58	-6.21	-0.07	1.01	2090
Combined Impact	-4.10	-6.85	-0.85	1.05	2092
Increase in Standard Deviation By 25 Percent					
Variance Degree Days 8-29°C	-1.43	-6.46	-0.43	0.68	1823
Sum Degree Days 29°C	-9.18	-14.39	-0.05	2.38	2090
Combined Impact	-10.48	-15.94	-2.51	2.47	2092
Increase in Standard Deviation By 50 Percent					
Variance Degree Days 8-29°C	-3.14	-13.78	-0.95	1.47	1821
Sum Degree Days 29°C	-18.81	-27.13	0.49	4.34	2088
Combined Impact	-21.35	-30.29	-6.65	4.51	2092
Increase in Standard Deviation By 100 Percent					
Variance Degree Days 8-29°C	-7.34	-29.95	-2.26	3.30	1808
Sum Degree Days 29°C	-36.96	-48.14	4.74	7.13	2084
Combined Impact	-41.54	-55.17	-17.60	7.32	2092

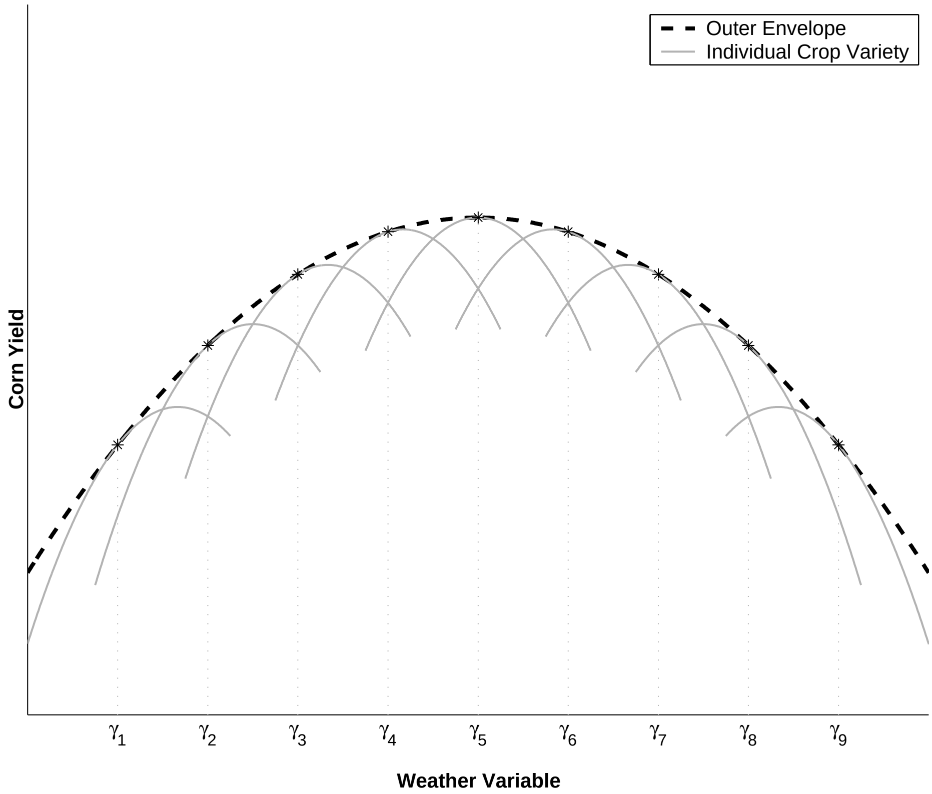
Notes: Table uses same approach as Table 4 except that the first twelve rows use a linear specification for degree days above 29°C, while the last twelve use a quadratic specification (compared to the square root used in Table 4).

Table 6: Changes in Expected Corn Yields Due to Changing Robustness of Plants for a Shift in Mean Temperatures while Holding Inter-annual Variance Constant (Percent).

Variable	Mean	Min	Max	σ	Gainers	Losers
Predictions for the Medium-term (2020-2049)						
Hadley HCM3-B1	-0.12	-7.56	5.13	1.10	113	251
Hadley HCM3-B2	-0.22	-9.67	5.50	1.41	107	258
Hadley HCM3-A2	-0.21	-9.47	5.57	1.38	105	273
Hadley HCM3-A1	-0.15	-8.98	6.05	1.26	106	256
Predictions for the Long-term (2070-2099)						
Hadley HCM3-B1	-0.70	-15.71	7.17	2.33	69	330
Hadley HCM3-B2	-1.05	-19.04	7.24	2.97	60	356
Hadley HCM3-A2	-2.97	-25.70	7.21	5.21	42	347
Hadley HCM3-A1	-5.83	-29.19	6.63	7.25	29	554

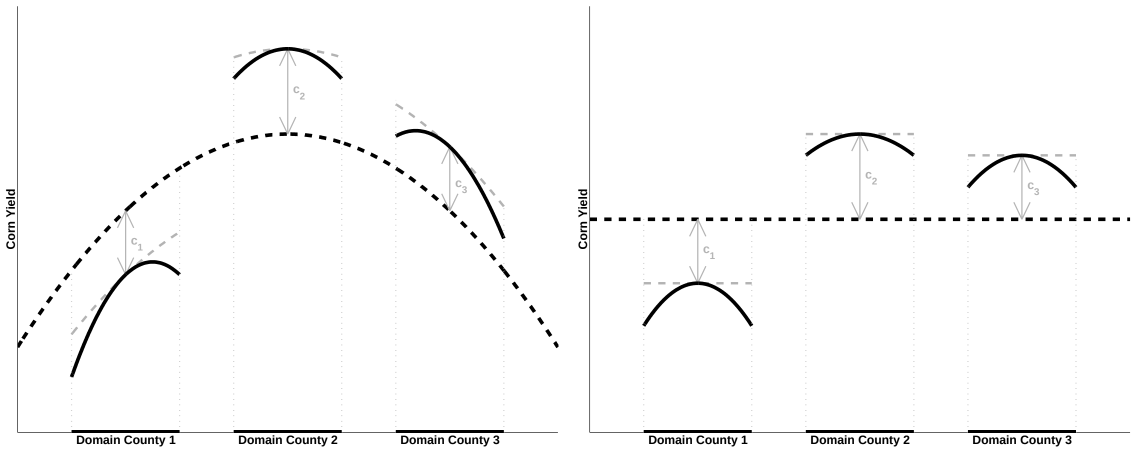
Notes: Table lists the percentage impact on corn yields for increases in temperatures as outlined in the Special Report on Emissions Scenarios (SRES) for the IPCC 3^{rd} Assessment Report (Nakicenovic, ed 2000). The rows are ordered from the lowest to the largest increase in average temperatures. The first four columns give the mean, minimum, maximum, and standard deviation of the impacts for the 2092 counties used in the first column of Table 2. The last two columns give the number of counties with statistically significant gains and reductions at the 95% level after adjusting for spatial correlation.

Figure 1: Yield as a Function of Weather - Illustrating the Possibility of Adaptations



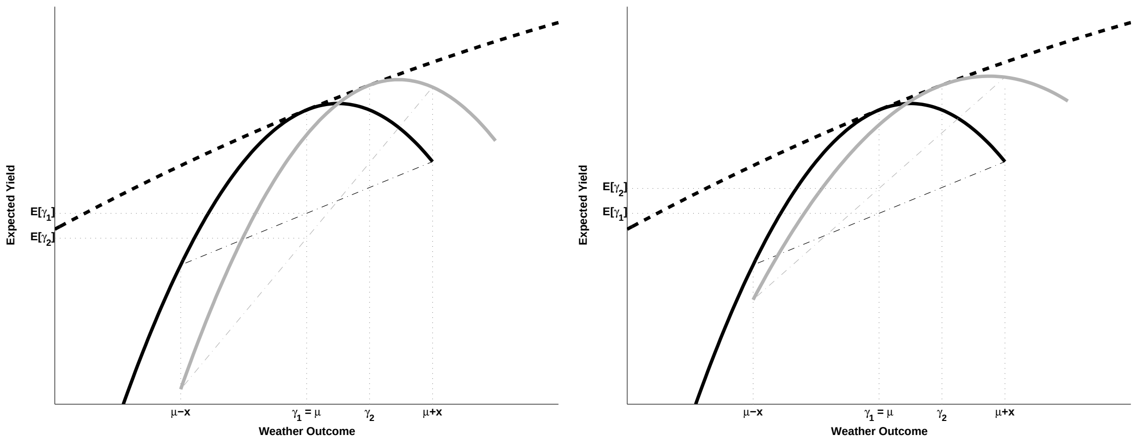
Notes: The above graph illustrates the adaptation potential to various climates. The x-axis can be any weather variable, e.g., temperature or degree days, while the y-axis displays yields. Individual varieties peak at various climates. The point of tangency between the yield function of an individual variety and the outer envelope is denoted by γ_i. For example, if the weather were known to be γ_3, it would be best to grow the variety that is tangent to the outer envelope at γ_3, as it will result in the highest yield. Two facts are noteworthy: First, due to the time-lag between planting (spring) and weather realization (summer), a farmer might grow variety γ_3 (i.e., the one that is tangent to the router envelope at γ_3 but weather turns out to be γ_4. Hence the yield will be suboptimal. Second, the first-order effect of a weather change at the average weather (climate) can be non-zero, i.e., farmers in cooler climates are predicted to welcome warmer-than-average weather outcomes while farmers in hot climates should welcome cooler-than-average weather outcomes.

Figure 2: Yield as a Function of Weather - Allowing for County Fixed Effects



Notes: The above two graphs motivate the relationship we are estimating. The x-axis can be any weather variable, e.g., temperature or degree days, while the y-axis displays yields. For illustrative purposes three counties with distinct weather ranges are displayed. The dashed black line displays the outer envelope of attainable corn yields. The c_i are county fixed effects that shift this envelope up or down. The tangency occurs if actual weather equals the optimal weather requirement of the variety. The solid black line indicates that there will be additional reductions in corn yields if weather turns out to be different from the optimal weather for the specific variety. The left graph displays the case when the first-order effect at the point of tangency is non-zero, while the right graph displays the case where it is zero. Note that in the right graph the effects of changing climate conditions are captured by county fixed effects.

Figure 3: Modeling the Choice of the Optimal Crop Variety



Notes: The above two graphs motivate the optimal crop choice. The x-axis can be any weather variable, e.g., temperature or degree days, while the y-axis displays yields. The dashed black line displays the outer envelope of attainable corn yields, while the solid lines indicate that there will be additional reductions in corn yields if weather turns out to be different from the optimal weather for the specific crop variety. Specifically we assume that there are only two weather outcomes with equal probability: $\mu - x$ and $\mu + x$. Each graph displays the expected yield if variety $\gamma_1 = \mu$ (black line) and γ_2 (grey line) are chosen. The left graph displays the case where the curvature of the solid lines is the same for both crop varieties and hence the yield is maximized by choosing variety $\gamma_1 = \mu$, as $\mathbb{E}[\gamma_1] > \mathbb{E}[\gamma_2]$. The right graph displays a case where variety γ_2 is more robust, i.e., resulting yield losses due to weather deviations are less for variety γ_2 than for γ_1. It now becomes optimal to grow a crop $\gamma_2 \neq \mu$ as $\mathbb{E}[\gamma_2] > \mathbb{E}[\gamma_1]$

Figure 4: Number of Of Reported Corn Yields in the Years 1950-2004.

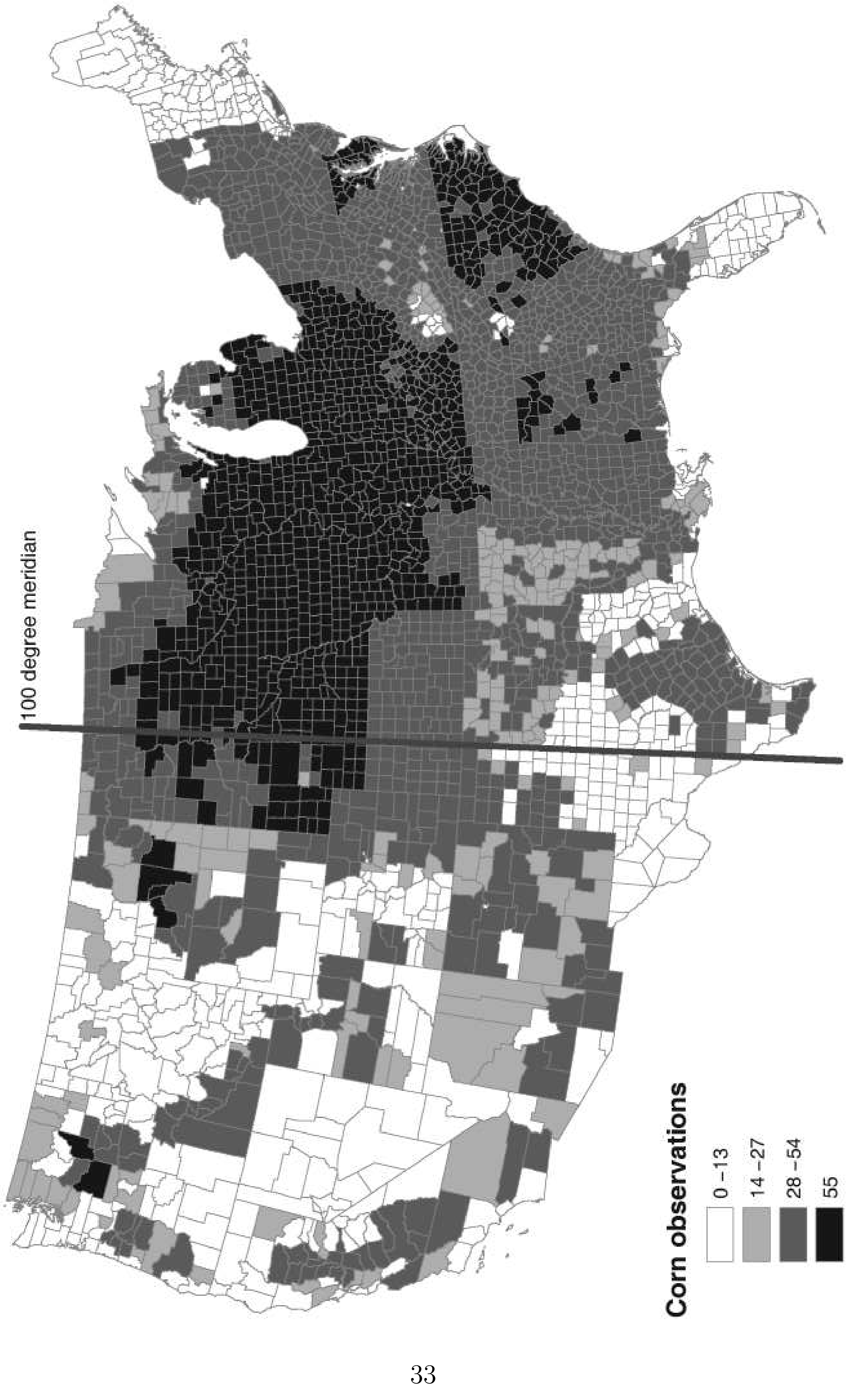
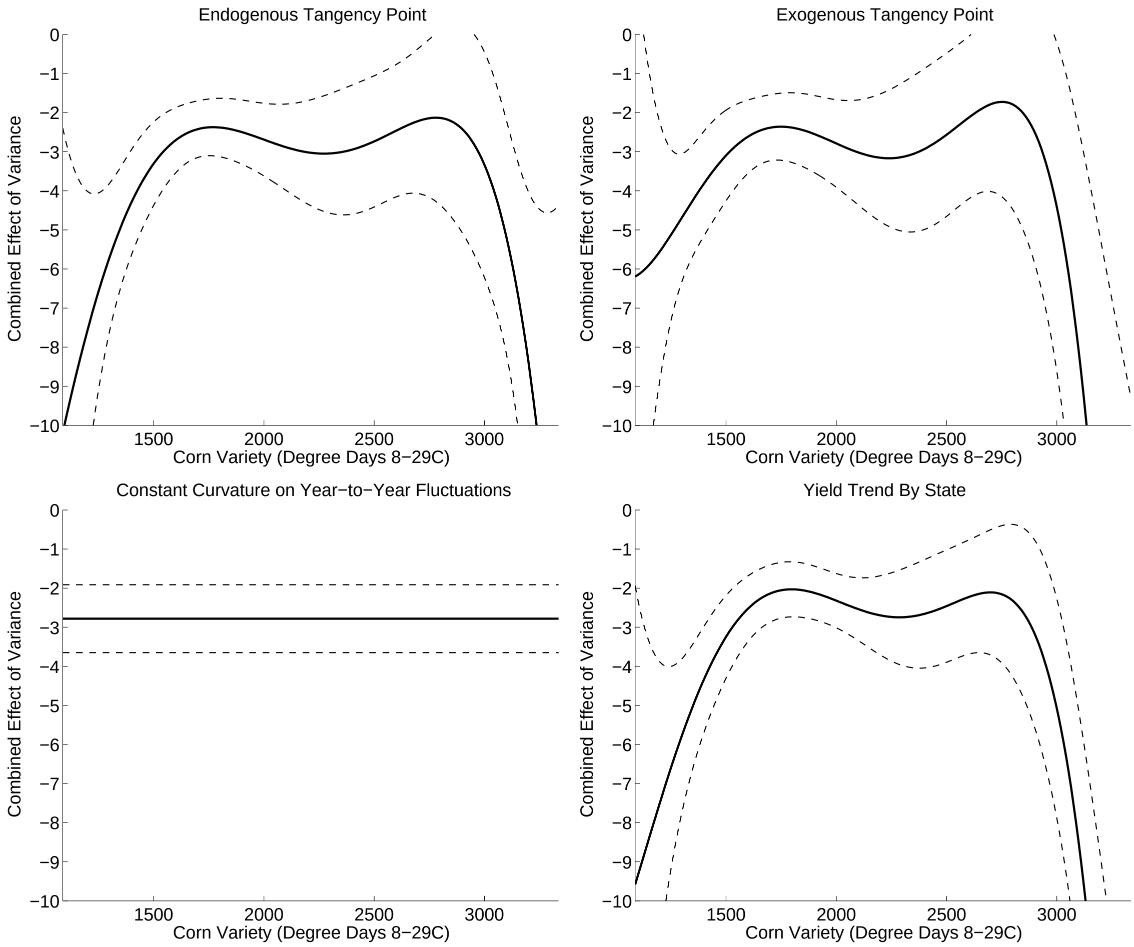
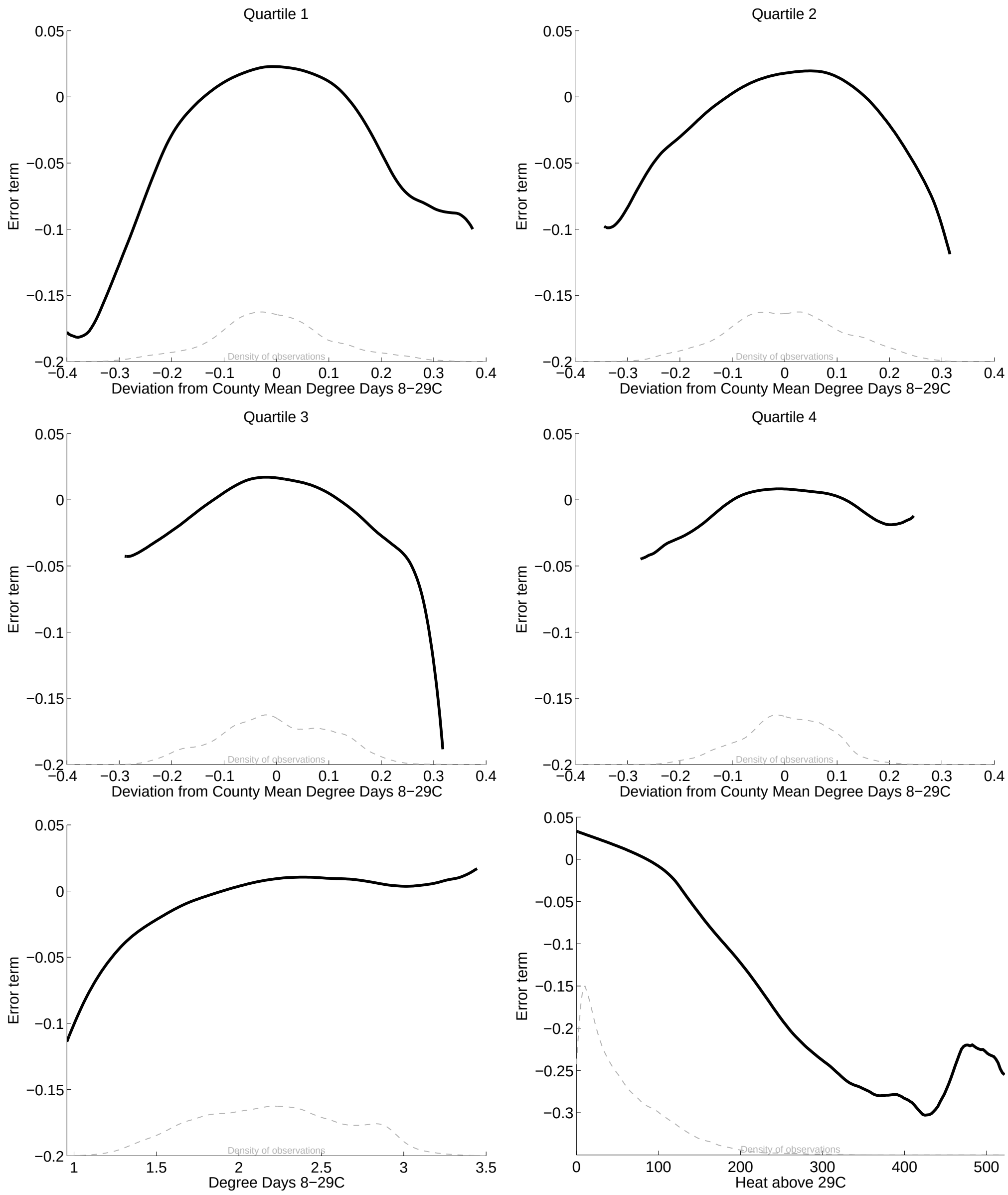


Figure 5: Within-curvature as a Function of Planted Corn Variety (Degree Days 8-29°C)



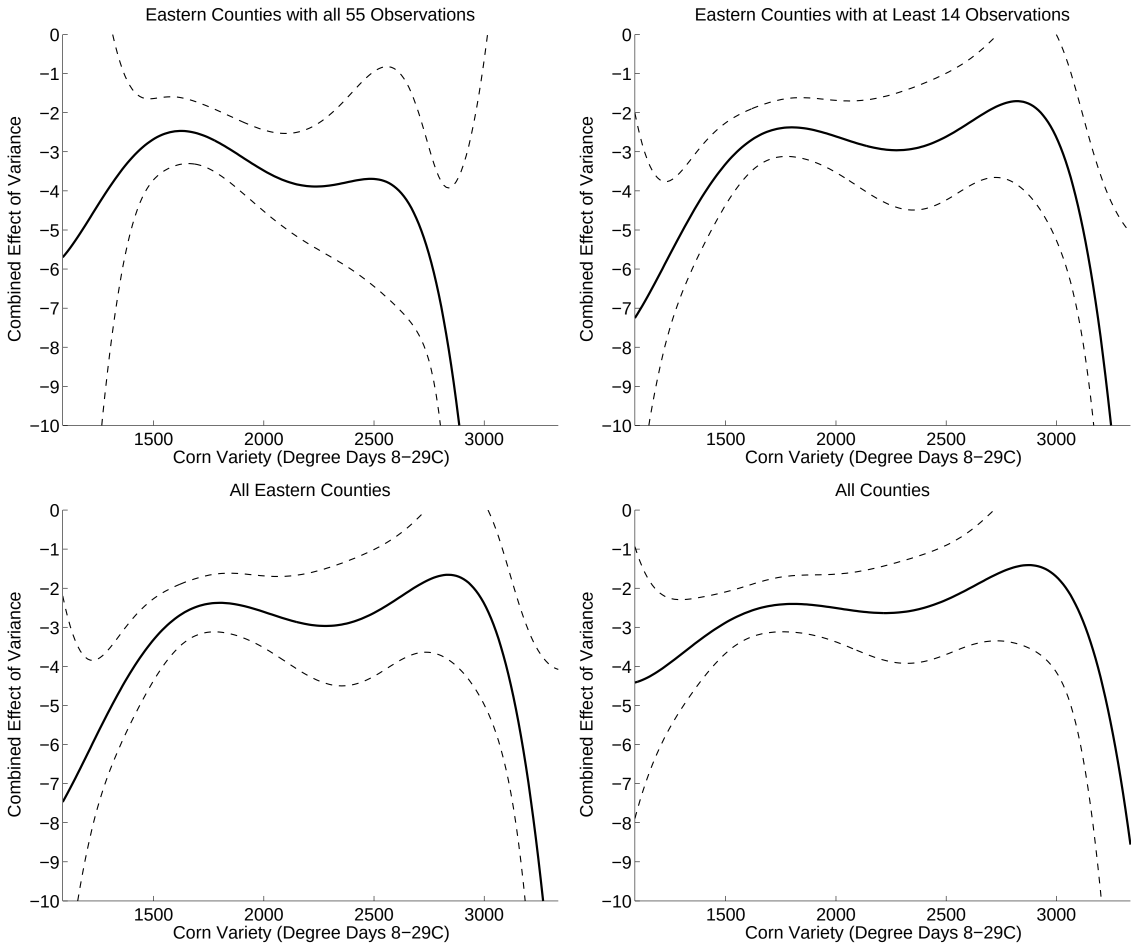
Notes: Expected yields $\mathbb{E}[y_{it}]$ include a multiplicative term on the variance of weather in county i, i.e., $[\beta_2 + \beta_3(\gamma_i)] * \sigma_i^2$, where γ_i is the point of tangency with the outer envelope. The above panels display the term $\beta_2 + \beta_3(\gamma_i)$ as solid line, and a 95% confidence band as dashed lines after adjusting for spatial correlation. Panels displays results corresponding to columns (1) through (4) of Table 2. The top left panel allows for an endogenous tangency point between individual corn varieties and the outer envelope. The top right panel forces this tangency to occur at average weather (climate) in a county. The lower left panel assumes a uniform within-curvature, while the lower right panel uses quadratic yield trends by state instead of year fixed effects.

Figure 6: Local Regression to Test Functional Form Assumptions



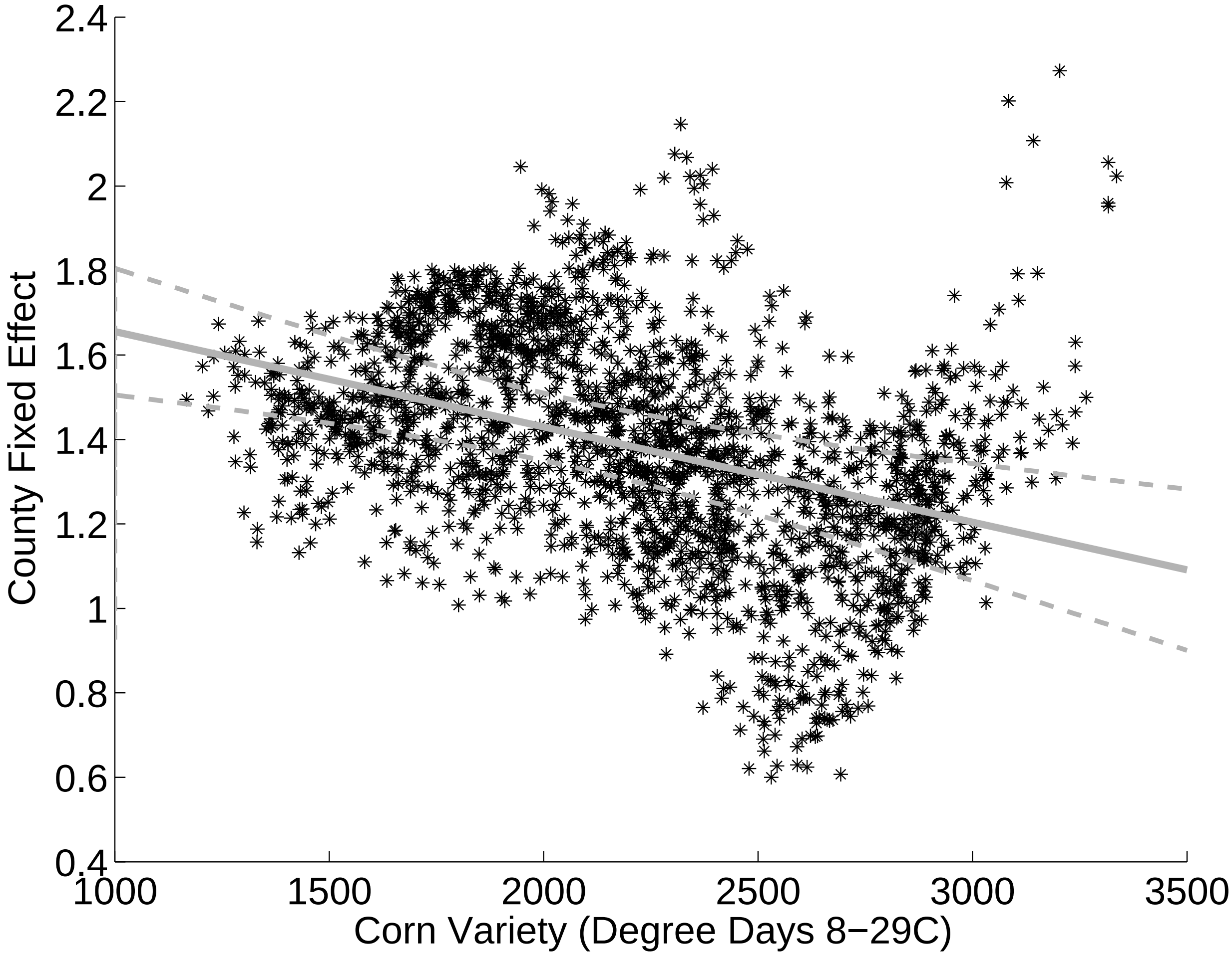
Notes: The above graphs use coefficient estimates from the preferred model (column 1 of Table 2). In each graph, a local regression of the error terms (using Epanechnikov weights) is plotted against the explanatory variable that was omitted from the model when the error terms are predicted. In the first two rows, deviations from county averages are omitted ($\beta_3(\gamma_i)[x_{it} - \gamma_i]^2$) when the error terms are predicted and the data is split into four quartiles according to the average climate of a county. The bottom left graph omits the outer envelope ($\beta_1 x_{it} + \beta_2 x_{it}^2$), while the bottom right graph omits the effect of harmful heat waves (δz_{it}). Bandwidths are 0.15 for the top four graphs, 0.5 for bottom left, and 125 for the bottom right graph.

Figure 7: Within-curvature as a Function of Planted Corn Varieties (Degree Days 8-29°C) for Various Subsets of the Data



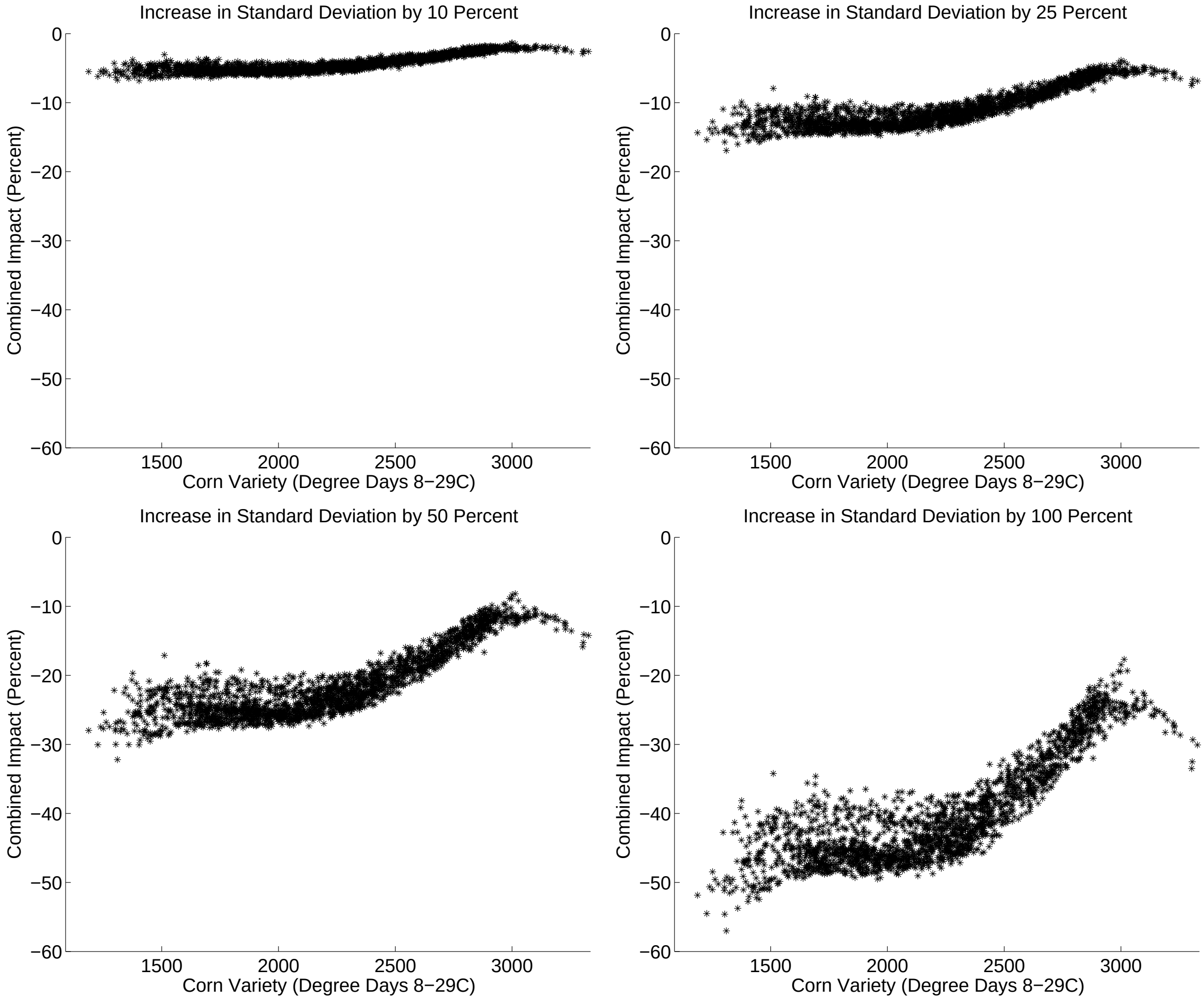
Notes: Expected yields $\mathbb{E}[y_{it}]$ include a multiplicative term on the variance of weather in county i, i.e., $[\beta_2 + \beta_3(\gamma_i)] * \sigma_i^2$, where γ_i is the point of tangency with the outer envelope. The above panels display the term $\beta_2 + \beta_3(\gamma_i)$ as solid line, and a 95% confidence band as dashed lines after adjusting for spatial correlation. Panels displays results corresponding to columns (1) through (4) of Table 3. All panels allow for an endogenous tangency between individual crop varieties and the outer envelope.

Figure 8: Fixed Effects Plotted Against Mean Degree Days 8-29°C



Notes: Fixed effects are shown as black dots. The solid grey line displays the result from a linear model regressing county fixed effects on the climate in a county. The 95% confidence band after adjusting for the spatial correlation of the error terms is displayed as dashed grey lines. The data set includes all counties east of the 100 degree meridian with at least 28 reported yields in the years 1950-2004.

Figure 9: Distribution of Changes in Expected Corn Yields for Various Increases in the Variance of Temperatures



Notes: Stars indicate the impacts of an increase in variance of both minimum and maximum temperature as function of the grown variety. Impacts are show for the 2092 counties with at least 28 observations east of the 100 degree meridian.