Inter-annual Weather Variation and Crop Yields

Wolfram Schlenker

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Abstract

There has been a sharp increase in the frequency of extreme weather events in recent years. 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 crops 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 crop 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 crops that more robust to variation. Second, the elasticity of reductions in expected yields with respect to increases in the standard deviation of weather fluctuations is -0.4.

While increases in mean temperatures show the largest negative impact for regions with warm average climates, the largest negative impacts under an increase in the variance would be found in cooler and moderate-temperate regions. Since most farmers are currently offered subsidized crop insurance, an increase in weather variation also directly translates into added government payments.
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). On August 29, 2005, hurricane Katrina devasted New Orleans and resulted in record damages. Similarly, a heat wave scorched Europe in August 2004 and resulted in the warmest August ever recorded in the northern hemisphere. Only 18 months later, the winter of 2005/2006 brought historic low temperatures to large parts of Eastern Europe and Russia. These events have started a discussion whether we are entering a new regime of increased weather variability.

Several authors argue that an increase in extreme weather outcomes appears likely, yet it is very difficult to detect a statistically significant trend.\(^1\) 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 as staff members to assess insurance risks under various climate scenarios. Hence the market recognizes that these effects might potentially be large and significant and warrant further study.

This paper examines the link between weather variability and crop yields. 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 focuses exclusively on the effects of a shift in mean weather outcomes (i.e., climate). We examine the impact 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 subspecies 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.\(^2\)

However, while mean weather (climate) is known, actual weather outcomes are random

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\(^1\)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.”

\(^2\)For a more elaborate discussion of degree days, see the data section below.
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 shift in mean weather 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 crop variety or use a different planting practice. This is illustrated in Figure 1, which displays crop yields of individual crop varieties in grey and the outer envelope of maximum attainable crop yields as a dashed black line. If a farmer were to know that weather outcome will be $\gamma_3$ for sure, he/she will commit to the crop variety that is on the outer envelope for weather outcome $\gamma_3$. If weather turns out to be $\gamma_2$ or $\gamma_4$ instead, the grey yield curve lies within the outer envelope and it would have been better to chose a different crop variety.

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 crop yields to simultaneously estimate the outer envelope of crop 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 weather outcomes would have been known in advance. The drop inside the outer envelope occurs because a suboptimal species was grown for the particular weather outcome. Our setup emphasizes that weather deviations from the point of tangency between individual yield functions and the outer envelope are responsible for additional crop losses, and larger deviations result in further productivity losses. We allow these additional productivity losses due to weather fluctuations to vary by crop variety. Another unique feature of our estimation strategy is that we allow for an endogenous choice of crop variety, where we index a crop variety by its tangency point with the outer envelope. If the effects of inter-annual variation on crop losses is uniform for all climates, farmers will choose a point of tangency that equals the average growing condition. If, however, various crop varieties exhibit changing robustness to weather fluctuations, farmers might decide to grow a crop 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.

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 unrobust, fluctuations will push observed yields within
the outer envelope. There are hence two channels through which climate change can alter crop yields: First, if the robustness of plants to withstand varies between crop 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 plant that might be more or less robust to these presumably constant fluctuations. Second, inter-annual variations might increase as outlined at the beginning of this paper. If the relationship between weather and yields of an individual crop variety are concave, an increase in the variance of year-to-year fluctuations will unambiguously reduce expected yields by Jensen’s inequality.

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 crop 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 crop 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 crop variety and regression coefficients. The empirical results are used to identify the consequences of changes in mean and variance of the weather distribution 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. See 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 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.

Time series data of crop yields traditionally have been used to examine how year-to-year weather fluctuations influence yields, either for specific climatic regions 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.\footnote{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.} Schlenker and Roberts (2006) link corn yields to weather outcomes over a 55 year period and find a highly significant nonlinear relationship. All of this second set of empirical studies do not capture farmer adaptations to various climates, as these 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. Assume there is a continuum of crop varieties that can be grown by a farmer. These crop varieties are indexed by \( \gamma_i \), where \( \gamma_i \) is the point of tangency between the yield function of a particular crop variety and the outer envelope of all crop 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 \( z_{it} \), and a county-fixed effect \( c_i \), i.e.,

\[
y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (\gamma_i) [x_{it} - \gamma_i]^2 + z_{it} \delta + c_i + \epsilon_{it}
\]

Note that yields in a particular year depend on the weather index \( x_{it} \) in two ways: First, the cross-sectional component specifies an outer envelope of the maximum attainable yield if the optimal crop variety is grown, i.e., \( y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + z_{it} \delta + c_i \). 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 \( \gamma_i \).

The additional crop 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 crop variety \( \gamma_i \) (in spring), and nature than randomly draws a weather outcome \( x_{it} \) that might differ from \( \gamma_i \). 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" crop instead. Unfortunately, a farmer can only base his or her planting decisions on expectations about the weather, as the ultimate outcome is random.

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 \( \gamma_i \) 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 \( \gamma_i \) would be zero, i.e., the yield function of the specific crop variety would peak at \( \gamma_i \) 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 \( \bar{y}_i = c_i + \beta_1 \bar{x}_i + \beta_2 \bar{x}_i^2 + \bar{z}_i \delta \) (where \( \bar{y}_i \) is the average log yield, \( \bar{x}_i \) the average weather, or climate, over all \( x_{it} \), and \( \bar{z}_i \) 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. The purpose of this paper is to disentangles the outer-envelope of attainable crop yields for various crop-varieties from year-to-year weather fluctuations 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 \( \gamma_i \). Assume weather in county \( i \) is distributed with mean \( \mu_i \) and standard deviation \( \sigma_i \). Hence the expected yield as a function of the chosen crop variety \( \gamma_i \) is

\[
E[y_{it}] = E[ \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (\gamma_i)x_{it}^2 + \bar{z}_i \delta + c_i + \epsilon_{it} ]
\]

\[
= \beta_1 \mu_i + \beta_2 [\mu_i^2 + \sigma_i^2] + \beta_3 (\gamma_i) [\sigma_i^2 + [\mu_i - \gamma_i]^2] + E[ \bar{z}_i \delta ] + c_i
\]

The derivation is given in the appendix. Maximizing the expected yield with respect to the chosen crop variety \( \gamma_i \) we get the following first-order condition

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

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

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 $\gamma_i$

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

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 $\sigma_i^2$. Recall that $\beta_3'(\gamma_i)$ measures the change in how a crop variety can withstand 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 crop 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 weather shocks (i.e., the same curvature) as shown in the left panel, the largest expected yield will be obtained for the crop variety that is tangent to the outer envelope at the mean weather variable. The right panel displays an example where the warmer-weather variety $\gamma_2$ (grey line) is more robust to weather fluctuations than the colder-weather variety $\gamma_1$ (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 $\mu = \gamma_2$, the black line lies above the grey line, indicating that if the weather had no variability but would always equal the mean weather outcome, crop variety $\gamma_1$ would be preferable. However, given that the grey line has less curvature, the expected yield is higher for $\gamma_2$ 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 $z_{it}$ 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 $8^\circ\text{C}$, and the upper bound for corn was found to be $29^\circ\text{C}$ (Schlenker and Roberts 2006).\footnote{A day of 5, 8, 10, 29, and 30 degrees Celsius would constitute 0, 0, 2, 21, and 21 degree days respectively.} 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 $z_{it}$ therefore include the square root of degree days above 29°C. The square root has a higher R-square than a quadratic specification. It is also preferable on theoretical grounds as it implies decreasing marginal damages that remain negative, while a positive quadratic term implies that additional heat eventually becomes beneficial, which is at odds with empirical observations.\(^5\) One noteworthy fact is that these harmful effects appear consistent for northern and southern counties, suggesting that there is limited potential for adaptation. 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 $z_{it}$. In contrast to the 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 $E[z_{it}]$ and lower expected yields, but the distinction to $x_{it}$ is that this loss is not impacted by the choice of crop variety. Other control variables included in $z_{it}$ 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 the inner and outer envelope as well as the point of tangency $\gamma_i$ in Section 3. Most of the time $\gamma_i$ turns out to be close to $\mu_i$. However, an inaccurate choice of $\gamma_i$ will give inconsistent estimate for $\beta_3$, 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\(^5\)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.
this study we focus on corn, one of the crops with the largest planting area. Furthermore, corn is grown in various climatic regions as shown in Figure 4.

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. Note that 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 include 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 utilized 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. The number of degree days are summed over all days in the growing season. Table 1 also gives the average absolute

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6In 2002, roughly 20% of total cropland in the United States was used to grow corn.
7The former constitutes 12°C - 8°C = 4 degree days, while the latter are only 10°C - 8°C = 2 degree days.
8We use the 6-months period April through September as planting dates vary between regions, but our
deviation from a county’s mean 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 heat. 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 quadratic functional form. The third climatic variable we include is total precipitation during this six month period April-September as well its squared term. The presumption is that there is an interior maximum, as too much or too little precipitation is harmful to a plant. It should be noted that we use log yields as the dependent variable and hence our independent variables interact multiplicatively.

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, there are several corn varieties that 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 crop. 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 $\gamma_i$ is the optimal degree days requirement.

Other climatic variables included in the control variables $z_{it}$ 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 $z_{it}$ is that the former allows for adaptation, while the negative impacts of the latter can not be influenced by choosing various
crop varieties. Other controls in \( z_{it} \) are year fixed effects to account for the almost threefold increase in average yields in our data set. The error terms \( \epsilon_{it} \) 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

\[
y_{it} = \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (\gamma_i) [x_{it} - \gamma_i]^2 + z_{it} \delta + c_i + \epsilon_{it}
\]

The challenge in the estimation is the endogeneity of the optimal crop variety \( \gamma_i \). The optimal crop variety depends on how the curvature for year-to-year weather fluctuations \( \beta_3 \) changes in degree days 8-29°C. However, \( \beta_3 \) can only be estimated consistently if yearly weather outcomes \( x_{it} \) are demeaned by the correct point of tangency \( \gamma_i \). Hence we need to estimate them jointly.

A simple example will motivate this point: \( \beta_3 \) 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 \( \beta_3 \) 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. The outer envelope captures that warmer-than-average weather outcomes are welcomed in cooler climates, for the same reason that colder-than-average weather outcomes are welcomed in hot climates. If the curvature of year-to-weather weather deviations is constant for all climates, it is best to plant the crop variety \( \mu_i \) that lies on the outer envelope at the mean weather outcome in a county \( \mu_i \).

If, on the other hand, curvature \( \beta_3 \) were to change with average weather, a farmer might be willing to grow a crop that is on the outer envelope at a point different from the average climate \( \mu_i \). This point is illustrated in Figure 3. The intuition is simple: Recall that the curvature \( \beta_3 \) determines how harmful yearly weather deviations caused by uncertain weather outcomes are on crop yields. If weather outcomes were fully predictable, it would surely be best to grow a crop that is on the outer envelope at the certain weather outcome. However, given real-world uncertainty overshadowing agricultural production, the robustness of plants to year-to-year weather fluctuations becomes important. If the harmful impact of weather deviations is changing between various crop varieties, than a farmer might be willing to grow a crop that would be suboptimal under perfectly predictable weather (as its yield at the average weather is inside the outer envelope, e.g., the grey line in the right panel of
Figure 3 is below the black line at $\mu$ but more robust to year-to-year weather fluctuations as measured by $\beta_3$. In summary, choosing $\gamma_i \neq \mu_i$ can be optimal if the resulting crop variety is more robust than $\gamma_i = \mu_i$.

We hence allow for an endogenous choice of $\mu_i$ 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.\(^9\)

The results for the preferred model are given in the first column of Table 2. Note that the outer envelope of degree days $8 - 29^\circ$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.\(^{10}\)

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 $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_m]$ to approximate $\beta_3(\gamma_i) = \beta_3[1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i)]$, where $T_j()$ is the $j^{th}$-order Chebyshev polynomial. The reported coefficient on ”degree days $8 - 29^\circ$C deviation squared” in Table 2 is the term $\beta_3$. 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 $\alpha$ 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

\(^9\)We use different order Chebyshev polynomials but obtain similar results.

\(^{10}\)The approach of Conley (1999) is an application of Newey and West (1987). Accordingly, we use a Bartlett window in the longitude and latitude dimensions with a cutoff value of 5 degrees, or 350 miles. We force the identification to come from contemporaneous correlation of the error terms in our panel data set.
\( \beta_2 + \beta_3(\gamma_i) \) 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 withstanding annual 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 24.8 inches, which is close to predictions obtained in laboratory experiments.

Columns two to four in Table 2 uses various sensitivity 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 uses as tangency point between inner and outer envelope that is exogenously fixed at the mean number of degree days 8-29°C in each county. Recall that a farmer has an incentive to grow a crop 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 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 unduly restrictive in light of the other panels in Figure 5. The impact on remaining coefficients, however, is limited. Finally, column (4) in Table 2 and the bottom 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 24.8 inches 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.

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 heat waves less harmful, which is shown in the bottom right graph of Figure 6 that displays the corresponding within-curvature on the squared deviation 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 should observe fixed effects to vary systematically in the variable degree days 8 – 29°C. The fixed effects are displayed in Figure 7, 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.
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 crop yields, which, to our knowledge, have not been examined before. Year-to-year fluctuations enter expected yield in two distinct ways through the terms \( [\beta_2 + \beta_3 (\gamma_i)] \sigma_i^2 + \mathbb{E}[z_{it}] \).

First, there is some indication that climate change will increase inter-annual variation in weather as pointed out above. An increase in the variance \( \sigma_i^2 \) will lower expected yields as crop yields 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° (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 incentive to adapt mitigation measures given that high temperatures are more frequently observed. 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 \( \mathbb{E}[z_{it}] \). Table 4 reports the decrease in yields attributable to the increased variance \( \sigma_i \), while Table 5 reports the percent impacts due to a change in the grown crop varieties.11 The distribution of impacts as a function of the current climate is displayed in Figure 8. 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 larger for cooler counties that for warmer counties. While it is true that the increase in hot temperatures is larger for counties who have higher temperatures to begin with, our model specification includes the square root of degree days 29°C.12 Such a specification is inline with the concept of decreasing marginal damages of heat waves, i.e., consecutive heat waves have lower marginal damages. So even though the increase in degree days 29°C is larger in warmer climates, the marginal damage is lower. As it turns out, the second effect dominates the first, and the combined effect implies a smaller percentage reductions for warmer climates. While increases in mean temperatures primarily impact agriculture in currently

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11The 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 to mean temperatures for each day and derive the average number of degree days above 29°C during the growing season in each year.

12Recall that the model using a square root has a higher R-square than the one using a linear term.
warm regions, increases in the variance would hit cool and moderate-temperate regions more severely.

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. The combined effect can be quite 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$2.5million 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 crop 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 crop varieties that are less robust to weather variations. Table 5 reports changes in expected yields due to changing robustness of crops 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). In the medium term (2020-2049), impacts range from a 10% reduction in yields for moderate-temperate counties that become warmer and are forced to grow crop 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 crop 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 practices 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 crop in spring when actual weather outcomes for the main growing season (summer) are random and unknown.

We find that the outer envelope is comparable to the one obtained from cross-sectional studies regressing farmland values on climatic variables, controlling for soil quality and socio-economic variables. The advantage of using fixed effects is that the influence of soil and socio-economic variables does not have to be modeled explicitly as they are lumped together in the fixed effect.

Moreover, year-to-year fluctuations in weather result in additional yield losses. 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 crop variety whose yield lies strictly inside the outer envelope of possible adaptation 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 crop variety with a tangency point at the outer envelope different from the mean weather outcome is largest.

We next examine the implications of inter-annual weather variation on crop 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 a warming implies that crop varieties will become more (less) robust to weather fluctuations, even holding weather variation constant. This effect arises as a warming implies that farmers will switch to different crop varieties that are more (less) robust to weather fluctuations, respectively. 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 crop 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. A potential reduction 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 crop 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 fairly controversial (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 grown in various climatic regions.
References


6 Appendix

6.1 Derivation of expected yield

The expected yield in county $i$ becomes

$$\mathbb{E}[y_{it}] = \mathbb{E} \left[ \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (\gamma_i) [x_{it} - \gamma_i]^2 + z_{it} \delta + c_i + e_{it} \right] = \beta_1 \mathbb{E} [x_{it}] + \beta_2 \mathbb{E} [x_{it}^2] + \beta_3 (\gamma_i) \mathbb{E} [[x_{it} - \gamma_i]^2] + \mathbb{E} [z_{it}] \delta + c_i$$

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

$$\mathbb{E}[y_{it}] = \beta_1 \mu_i + \beta_2 [\mu_i^2 + \sigma_i^2] + \beta_3 (\gamma_i) \mathbb{E} [[[x_{it} - \mu_i + \mu_i - \gamma_i]^2] + \mathbb{E} [z_{it}] \delta + c_i$$

$$+ \beta_3 (\gamma_i) \mathbb{E} [[[x_{it} - \mu_i]^2] + \mathbb{E} [[[x_{it} - \mu_i][\mu_i - \gamma_i]] + \mathbb{E} [[[\mu_i - \gamma_i]^2]]$$

$$= \beta_1 \mu_i + \beta_2 [\mu_i^2 + \sigma_i^2] + \beta_3 (\gamma_i) [\sigma_i^2 + [\mu_i - \gamma_i]^2] + \mathbb{E} [z_{it}] \delta + c_i$$

The first-order condition for the optimal crop variety $\gamma_i$ hence is

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

In the numerical implementation we look for the minimum of the following function for each of the counties $i$ (groups) in our data set\(^{13}\)

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

with the following gradient and second derivative

$$f'(\gamma_i) = 2 [\beta_3' (\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2] - 2 \beta_3 (\gamma_i) [\mu_i - \gamma_i] [\beta_3'' (\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2] - 4 \beta_3' (\gamma_i) [\mu_i - \gamma_i] + 2 \beta_3 (\gamma_i)$$

$$f''(\gamma_i) = 2 [\beta_3' (\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2] - 4 \beta_3' (\gamma_i) [\mu_i - \gamma_i] + 2 \beta_3 (\gamma_i)]^2$$

$$+ 2 [\beta_3' (\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2] - 2 \beta_3 (\gamma_i) [\mu_i - \gamma_i] [\beta_3'' (\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2] - 6 \beta_3' (\gamma_i) [\mu_i - \gamma_i] + 6 \beta_3 (\gamma_i)$$

\(^{13}\)Using MATLAB’s routine fminunc.
6.2 Estimation procedure

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

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

Accordingly, the first-order condition of choosing the best crop-variety $\gamma_i$ is

$$\frac{\partial \psi(y_{it})}{\partial \gamma_i} = \beta_3 \left[ \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) \right] [\mu_i - \gamma_i]^2 - 2 \mu_i \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) + 2 \beta_3 \mu_i \left[ \sum_{j=1}^{m} \alpha_j T_j(\gamma_i) \right] [\mu_i - \gamma_i] = 0$$

### 6.2.1 Endogenous choice of crop variety

Total differentiation gives

$$0 = \left\{ \beta_3 \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) \left[ [\mu_i - \gamma_i]^2 + \sigma_i^2 \right] - 4 \beta_3 \mu_i \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) + 2 \beta_3 \mu_i \left[ \sum_{j=1}^{m} \alpha_j T_j(\gamma_i) \right] \right\} d\gamma_i$$

And hence

$$\frac{d\gamma_i}{d\alpha_k} = \frac{2 T_k(\gamma_i) [\mu_i - \gamma_i] - T'_k(\gamma_i) [\mu_i - \gamma_i]^2 + \sigma_i^2}{[[\mu_i - \gamma_i]^2 + \sigma_i^2] \left[ \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) \right] - 4 [\mu_i - \gamma_i] \left[ \sum_{j=1}^{m} \alpha_j T'_j(\gamma_i) \right] + 2 \left[ 1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i) \right]}$$

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 $\alpha, \beta, \delta$ is

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

Using the following abbreviations:

$$c_{it} = \left[ y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \beta_3 \left[ 1 + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\alpha)) \right] [x_{it} - \gamma_i(\alpha)]^2 - z_{it} \delta - c_i \right]$$
In a sensitivity check the point of tangency is exogenously set to equal the average outcome

\[ \sum_{i=1}^{m} \alpha_j T_j(\gamma_i(\alpha)) \]

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

\[
\frac{\partial S}{\partial \beta} = -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} x_{it} = -2e' x_1
\]

\[
\frac{\partial S}{\partial \beta} = -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} x_{it}^2 = -2e' x_2
\]

\[
\frac{\partial S}{\partial \delta} = -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} \beta_k \left[ T_k(\gamma_i(\alpha)) + \sum_{j=1}^{m} \alpha_j T_j(\gamma_i(\alpha)) \frac{d\gamma_i}{d\alpha_k} \right] (x_{it} - \gamma_i(\alpha))^2 \]

\[
\frac{\partial S}{\partial \gamma_i} = -2 \sum_{i=1}^{N} \sum_{t=1}^{T} e_{it} z_{it}^{(k)} = -2e' z_k
\]

We use the function \( \text{fminunc} \) in MATLAB to jointly solve for optimal crop varieties \( \gamma_i \) as well as parameters \( \alpha, \beta, \) and \( \delta \) 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

\[
S = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[ y_{it} - \beta_1 x_{it} - \beta_2 x_{it}^2 - \beta_3 \left( 1 + \sum_{j=1}^{m} \alpha_j T_j(\mu_i) \right) (x_{it} - \mu_i)^2 - z_{it} \delta - c_i \right]^2
\]
The partial derivatives become (where \( z^{(k)}_i \) is the \( k \)-th column of \( z \))

\[
\begin{align*}
\frac{\partial S}{\partial \beta_1} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i x_{it} = -2e'x_1 \\
\frac{\partial S}{\partial \beta_2} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i x_{it}^2 = -2e'x_2 \\
\frac{\partial S}{\partial \beta_3} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i \left[ 1 + \sum_{j=1}^{m} \alpha_j T_j(\mu_i) \right] [x_{it} - \mu_i]^2 = -2e'x_3 \\
\frac{\partial S}{\partial \alpha_k} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i \beta_3 T_k(\mu_i) [x_{it} - \mu_i]^2 \\
\frac{\partial S}{\partial \delta_k} &= -2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i z^{(k)}_i = -2e'z_k
\end{align*}
\]

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

\[
\begin{align*}
\frac{\partial^2 S}{\partial \beta_j \beta_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} x^{(j)}_{it} x^{(k)}_{it} = 2x'_j x_k \\
\frac{\partial^2 S}{\partial \beta_j \delta_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} x^{(j)}_{it} x^{(k)}_{it} = 2x'_j z_k \\
\frac{\partial^2 S}{\partial \beta_j \alpha_k} &= 2\beta_3 \sum_{i=1}^{N} \sum_{t=1}^{T} x^{(j)}_{it} T_k(\mu_i) [x_{it} - \mu_i]^2 \\
\frac{\partial^2 S}{\partial \beta_j \alpha_k} &= 2\beta_3 \sum_{i=1}^{N} \sum_{t=1}^{T} x^{(j)}_{it} T_k(\mu_i) [x_{it} - \mu_i]^2 - 2 \sum_{i=1}^{N} \sum_{t=1}^{T} \epsilon_i T_k(\mu_i) [x_{it} - \mu_i]^2 \\
\frac{\partial^2 S}{\partial \delta_j \delta_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} z^{(j)}_i z^{(k)}_i = 2z'_j z_k \\
\frac{\partial^2 S}{\partial \delta_j \alpha_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} z^{(j)}_i T_k(\mu_i) [x_{it} - \mu_i]^2 \\
\frac{\partial^2 S}{\partial \delta_j \alpha_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} z^{(j)}_i T_k(\mu_i) [x_{it} - \mu_i]^4 \\
\frac{\partial^2 S}{\partial \alpha_j \alpha_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} T_j(\mu_i) T_k(\mu_i) [x_{it} - \mu_i]^4 \\
\frac{\partial^2 S}{\partial \alpha_j \alpha_k} &= 2 \sum_{i=1}^{N} \sum_{t=1}^{T} T_j(\mu_i) T_k(\mu_i) [x_{it} - \mu_i]^4
\end{align*}
\]
Table 1: Descriptive Statistics

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<th>Mean</th>
<th>Min</th>
<th>Max</th>
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<th>$\sigma_{\text{within}}$</th>
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<td></td>
</tr>
<tr>
<td>Number of counties</td>
<td>2325</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Counties East of the 100 Degree Meridian With at Least 28 Observations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Yield</td>
<td>4.20</td>
<td>-3.19</td>
<td>5.32</td>
<td>0.53</td>
<td>0.40</td>
</tr>
<tr>
<td>Degree days 8-29°C (thousand)</td>
<td>2.20</td>
<td>0.96</td>
<td>3.45</td>
<td>0.45</td>
<td>0.10</td>
</tr>
<tr>
<td>Degree days 8-29°C deviation from mean</td>
<td>81.78</td>
<td>0.00</td>
<td>464.45</td>
<td>61.85</td>
<td>57.30</td>
</tr>
<tr>
<td>Square root degree days above 29°C</td>
<td>6.75</td>
<td>0.00</td>
<td>22.85</td>
<td>3.40</td>
<td>1.50</td>
</tr>
<tr>
<td>Precipitation (cm)</td>
<td>59.31</td>
<td>12.86</td>
<td>159.24</td>
<td>15.06</td>
<td>12.16</td>
</tr>
<tr>
<td>Number of observations</td>
<td>102029</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of counties</td>
<td>2092</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**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

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

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 heterogeneous 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 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, 3, and 4 we report the value $\beta_3$ 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 $T_j(\cdot)$ 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

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree Days 8-29°C</td>
<td>2.58</td>
<td>1.81</td>
<td>1.79</td>
<td>1.78</td>
</tr>
<tr>
<td></td>
<td>(9.55)</td>
<td>(8.26)</td>
<td>(8.23)</td>
<td>(9.43)</td>
</tr>
<tr>
<td>Degree Days 8-29°C Squared</td>
<td>-0.485</td>
<td>-0.301</td>
<td>-0.298</td>
<td>-0.301</td>
</tr>
<tr>
<td></td>
<td>(7.20)</td>
<td>(5.71)</td>
<td>(5.67)</td>
<td>(6.50)</td>
</tr>
<tr>
<td>Degree Days 8-29°C Deviation Squared</td>
<td>-3.80</td>
<td>-4.85</td>
<td>-4.64</td>
<td>-3.27</td>
</tr>
<tr>
<td></td>
<td>(5.73)</td>
<td>(5.40)</td>
<td>(5.38)</td>
<td>(5.14)</td>
</tr>
<tr>
<td>Degree Days 29°C</td>
<td>-1.07E-01</td>
<td>-9.57E-02</td>
<td>-9.57E-02</td>
<td>-8.98E-02</td>
</tr>
<tr>
<td></td>
<td>(16.50)</td>
<td>(17.65)</td>
<td>(17.72)</td>
<td>(18.20)</td>
</tr>
<tr>
<td>Precipitation</td>
<td>1.47E-02</td>
<td>1.02E-02</td>
<td>1.00E-02</td>
<td>8.72E-03</td>
</tr>
<tr>
<td></td>
<td>(7.97)</td>
<td>(7.02)</td>
<td>(6.96)</td>
<td>(6.85)</td>
</tr>
<tr>
<td>Precipitation Squared</td>
<td>-1.21E-04</td>
<td>-8.08E-05</td>
<td>-7.95E-05</td>
<td>-6.93E-05</td>
</tr>
<tr>
<td></td>
<td>(8.66)</td>
<td>(7.75)</td>
<td>(7.70)</td>
<td>(7.52)</td>
</tr>
</tbody>
</table>

**County fixed effects**

- Yes

**Year fixed effects**

- 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: Climate Change Impacts Due to an Increase in Weather Variation (Percent)

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

Notes: Table lists the percentage impact of inter-annual weather variation on crop yields under 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 29°C. The table uses the regression results of the preferred model in the first column of Table 2. The first four columns given 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: Impacts on Yearly Yields Due to Changing Robustness of Plants for a Shift in Mean Temperatures while Holding Inter-annual Variance Constant (Percent).

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

Notes: Table lists the impact of inter-annual weather variation on crop yields under various climate change scenarios as outlined in the Special Report on Emissions Scenarios (SRES) for the IPCC 3rd 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.
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 crop varieties peak at various climates. The point of tangency between the yield function of an individual crop and the outer envelope is denoted by $\gamma_i$. For example, if the weather were known to be $\gamma_3$, it would be best to grow the crop variety that is tangent to the outer envelope at $\gamma_3$, 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 $\gamma_3$ (i.e., the one that is tangent to the outer envelope at $\gamma_3$ but weather turns out to be $\gamma_4$. 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 shift this envelope up or down. The tangency occurs if actual weather equals the optimal weather requirement of the crop 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 crop 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 Optimal Crop Choice

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 indicates 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 crop variety $\gamma_1 = \mu$ (black line) and $\gamma_2$ (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 crop variety $\gamma_1 = \mu$, as $E[\gamma_1] > E[\gamma_2]$. The right graph displays a case where crop variety $\gamma_2$ is more robust, i.e., the resulting yield losses due to weather deviations is less than for $\gamma_1$. It now becomes optimal to grow a crop $\gamma_2 \neq \mu$ as $E[\gamma_2] > E[\gamma_1]$. 
Figure 4: Number of Reported Corn Yields in the Years 1950-2004.
Figure 5: Within-curvature as a Function of Planted Crop Variety (Degree Days 8-29°C)

Notes: Expected yield $E[y_{it}]$ includes a multiplicative term on the variance of weather in county $i$, i.e., $[\beta_2 + \beta_3(\gamma_i)] \times \sigma^2_i$, where $\gamma_i$ is the point of tangency with the outer envelope. The above two 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 endogenous tangency between individual crop 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: Within-curvature as a Function of Planted Crop Variety (Degree Days 8-29°C) for Various Subsets of the Data

Notes: Expected yield $E[y_{it}]$ includes a multiplicative term on the variance of weather in county $i$, i.e., $[\beta_2 + \beta_3(\gamma_i)] \ast \sigma_i^2$, where $\gamma_i$ is the point of tangency with the outer envelope. The above two 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 7: 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 8: Distribution of Impacts from an Increase in the Variance of Temperatures on Annual Yields

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