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Beyond Yield Response: Weather Shocks and Crop Abandonment

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***Selected Paper prepared for presentation at the 2019 Agricultural & Applied Economics Association
Annual Meeting, Atlanta, GA, July 21 – July 23***

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May 2019

Preliminary and Incomplete. Please do not cite without permission.

Abstract

The impacts of climatic factors on crop yields have been extensively examined in the literature on climate change impacts. However, how these factors affect decisions to abandon the crop is not well understood. This article uses a conceptual model to illustrate the mechanism of weather-induced crop abandonment, and empirically estimates the relationship between climatic factors and crop abandonment using US county-level data. A comparison of these estimates with the estimates of yield responses illustrates the rationale of the abandonment decisions. Further analyses show response heterogeneity in crop abandonment associated with different market conditions and certain institutional arrangement. The empirical results are consistent with the implications of the conceptual model.

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Under climate change, rising temperatures, changing precipitation patterns, and more frequent and severe extreme weather events are expected with high confidence in the future (Stocker et al., 2013). Climate change poses high global food security risks given the vulnerability of food systems (Wheeler and Von Braun, 2013). Understanding how climate change affects agriculture is critically important for making cost-effective climate policies (Nelson et al., 2009). The empirical estimate of crop yield response to changes in climatic factors has served as the central component for evaluating climate change impacts on agricultural production (Schlenker and Roberts, 2009; Miao, Khanna and Huang, 2016; Chen, Chen and Xu, 2016; Gammans, Mérel and Ortiz-Bobea, 2017, etc.). While evidence on yield response mainly characterizes the underlying damage function implied by crop bio-physics, its limitation on capturing growers' behavioral response has been acknowledged in the literature (Mendelsohn and Massetti, 2017; Carter et al., 2018).

An important responsive margin for the growers is to abandon the crop when weather conditions become particularly unfavorable. To an extreme, Texas farmers abandoned 62% of their planted cotton acreage in 2011 under a severe drought in the south-central United States (Rippey, 2015). Overlooking crop abandonment may underestimate the negative weather impacts on agricultural production, especially when extreme weather events become more frequent under climate change. Moreover, the social cost of crop abandonment could be much higher than yield losses given the predominance of subsidized crop insurance programs in countries like the United States. During the record-breaking drought in 2012, the US government budgetary cost of Federal crop insurance exceeded 13 billion dollars (USDA, 2018).

This article explores how climatic factors affect crop abandonment. I first use a stylized model to conceptually illustrate the mechanism. Under a weather shock, a grower may forgo harvesting if the expected crop revenues cannot justify the opportunity cost, mostly the variable cost of harvesting, even if the realized yield is not zero. At the regional level, the collection of these individual behaviors left-truncates the regional yield distribution, resulting in the lower-yield portion of land being unharvested. This truncation implies that the magnitude of the weather-induced crop abandonment is not necessarily proportional to the yield loss, as it is jointly determined by the shape of

yield distributions as well as the truncation cutoff implied by input and output prices.

Guided by the conceptual model, I empirically estimate the impacts of weather shocks on crop abandonment of US corn and soybeans. Utilizing daily weather information, for corn and soybeans, I flexibly explore the nonlinear relationship between the harvested ratios, measured by harvested over planted acres, and growing-season temperature accumulation, using a semi-parametric regression specification. Under a panel fixed effects model with flexible regional trends, the nonlinear relationship is identified by exploring the exogenous year-to-year variation of the climatic variables within counties and off state-level trends.

Both corn and soybean harvested ratios are positively affected by accumulating moderate heat, but corn is more responsive to heat accumulation at the low-range of moderate heat. The harvested ratios of both crops are highly sensitive to extremely high temperatures, namely beyond 37°C. However, there is no evidence for such a significant negative effect when the crops are exposing to temperatures just above 30°C, which contrasts with the sharp nonlinearity in yield responses occurred around 30°C. More precipitation appears to increase the harvested ratios in dry areas and decrease them in wet areas. The harvested ratio of corn is more responsive than soybeans, especially in terms of the positive effect detected for dry areas.

Building on the specification with widely used degree days variables, I evaluate the relationship between climatic factors and harvested ratios with an alternative specification. In addition to conventional growing and heat degree days variables, I include a new measure of extreme hot days, capturing the coupled heat and water stress in a growing season. Conditional on the negative effects of heat degree days, extreme hot days reduce corn and soybean harvested ratios, and the effects are both statistically and economically significant, which illustrates the importance of considering the coupled heat and water stress in this relationship.

Throughout the analysis, I compare harvested ratio estimates with yield estimates to infer the rationale of farmers' behavioral responses. The yield responses to moderate heat and cumulative precipitation are very similar for corn and soybeans. However, the harvested ratio of corn is more responsive than soybeans. In contrast, the yield impact of extremely high temperature is about three

times larger for corn, while the harvested ratio impact on corn is very similar to that on soybeans. The relatively higher per-acre revenue of corn partly explains these differences, as corn farmers are more incentivized to reap the benefits or cut back the loss through adjusting their harvested acres.

Further analyses show response heterogeneity in harvested ratios related to crop prices and the Federal crop insurance participation, consistent with implications of the conceptual model. I find suggestive evidence that the responses are partially mitigated in high price years, in line with the findings of comparing corn and soybean estimates as discussed above. There is also some indication of insurance augmenting the impact of extreme hot days on the harvested ratio of corn, echoing the discussion in Burke and Emerick (2016). However, different from Burke and Emerick (2016), I do not find insurance-related heterogeneous response in yields, likely due to the different variation of insurance participation used in this article.

This article contributes to the understanding of climate change impacts on agricultural production. The literature has largely focused on measuring the relationship between crop yields and climatic factors, and the results have been used for predicting climate change impacts on agricultural production in the medium and long run (e.g. Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Chen, Chen and Xu, 2016; Miao, Khanna and Huang, 2016). Given that total production is the product of yields and harvested areas, the response of the latter could confound the interpretation of yield responses as production changes (Iizumi and Ramankutty, 2015). In contrast to the vast literature on crop yields, studies on harvested areas are rare. One exception is Lesk, Rowhani and Ramankutty (2016), which finds that droughts lead to reduction in both yields and harvested areas. However, this study is based on country-level aggregate data. Using finer-scale county-level data, this article is able to more accurately gauge the magnitude of response in crop abandonment as compared to crop yields.

Making distinction between yield loss and harvested acreage reduction is also important on its own. By illustrating the mechanism of weather-induced crop abandonment with a conceptual model, this article highlights factors that may complicate the behavioral response of farmers regarding abandoning the crops. By linking crop prices with heterogeneous responses of crop

abandonment, this article builds on the understanding on how market outcomes influence market participants' behaviors to combat unexpected shocks. This article also provides evidence for understanding the role of certain institutional arrangements in environmental adaptation. Specifically, some results on corn abandonment builds on the discussion in Annan and Schlenker (2015) that the Federal crop insurance program may have created disincentives for climate change adaptation.

The article is organized as follows. The next section introduces a stylized model to illustrate the mechanism of how weather shocks affect harvested areas. Guided by the model, Section 2 lays out the empirical strategy, followed by a discussion of data in Section 3. Section 4 presents the estimation results of different regression specifications and discusses the implications by comparing different sets of estimates. The last section concludes.

1 A Stylized Model

Suppose crop yield y in a small area – for example, a county – is distributed as some density function $f(y)$. For any plot, the crop is harvested only if its realized profit justifies the opportunity cost of harvesting. Suppose the unit output price is p , and the harvesting cost per unit of land is c . The plot is harvested if and only if $py - c > 0$. For simplicity, the cost c is assumed to be uniform across growers in the small area. The net profit of growing and harvesting the crop subjects to a further deduction of planting cost incurred before any harvesting decision is made. However, for a fully rationale grower, the planting cost does not factor into the harvesting decision directly as it has become a sunk cost when the harvesting time arrives.

Scaling the total acreage of the small area to be one, the realized crop output is the integral of the yield distribution truncated at a minimum level of yield determined by the output price and harvesting cost, i.e.,

$$\text{total output of the small area} = \int_{c/p}^{+\infty} yf(y)dy. \quad (1)$$

Suppose a negative weather shock shifts the yield distribution to a lower level, and denote the new distribution as $f'(y)$. For simplicity, I assume $f(y)$ first-order stochastic dominates $f'(y)$,

reflecting that the weather shock shifts the entire yield distribution to a lower level. Holding all else equal, the net output loss incurred by the weather shock can be represented as

$$\begin{aligned} \text{shock-induced output loss} &= \int_{c/p}^{+\infty} y (f(y) - f'(y)) dy \\ &= \int_{-\infty}^{+\infty} y (f(y) - f'(y)) dy + \int_{-\infty}^{c/p} y (f'(y) - f(y)) dy, \end{aligned} \quad (2)$$

where the first term represents the net loss in total output associated with a shift of the entire yield distribution, and the second term is the additional output change associated with crop abandonment. If $f(y)$ first-order stochastically dominates $f'(y)$, the weather-induced additional abandoned portion will be non-negative, as conceptually illustrated by the shaded area in Figure 1. The weather-harvest relationship is complicated by two factors: the cutoff point c/p as well as the specific distribution forms of $f(y)$ and $f'(y)$, which implies that harvest responses to weather shock could be heterogeneous across years with high and low prices, and across places with potentially different yield distributions.

Figure 1: Additional Abandoned Acreage Share Induced by Weather Shock

Note: $f(y)$ and $f'(y)$ represent the pre-shock and post-shock yield distributions, respectively. Crops are abandoned if yields are below c/p . The shaded area indicates the additional abandoned acreage share induced by the negative weather shock.

2 Empirical Strategy

The empirical strategy of this article builds on a panel fixed effects estimation framework as the following,

$$y_{it} = f(\{T_{itd}, P_{itd}\}_{d=1}^D; \beta) + \delta_{1,s}t + \delta_{2,s}t^2 + \eta_t + \alpha_i + \varepsilon_{it}. \quad (3)$$

Throughout the empirical framework, i indexes counties, s indexes states, and t indexes years. y_{it} represents the agricultural outcome variable. To study harvesting decision, I use a harvest ratio, defined as the proportion of harvested acres over the total planted acres. Logarithmic crop yields are used in supplementary regressions to compare the results. Using d to index days, T_{itd} and P_{itd} represent daily temperature and precipitation, respectively. f is a transformation function that summarizes daily temperature and precipitation into a vector of annual weather variables, parameterized by a vector β .

Not all days are equally important within a year. It is reasonable to assume that pre-planting weather information only affects planting decisions but not harvesting decisions. Given that the marginal weather effects of interest are conditional on the planting decisions that have been made, the most relevant weather information comes from the period after planting and before harvesting. For convenience, I call this specific period as the *growing season* in this article. Therefore, the day-to-year aggregation of weather only considers weather realizations over the growing season, which can be more formally viewed as the f function imposing zero partial effects of weather on days outside the growing season. The specific forms of f are introduced in Section 4.

For the rest terms in equation (3), county fixed effects (α_i) absorb the effects associated with county-specific time-invariant factors so that county characteristics do not confound the identification. Year fixed effects (η_t) control for nationwide shocks in a particular year, like policy shocks related to the Farm Bill and expectation shocks related to the El Nino-Southern Oscillation. State-level quadratic trends characterize the long-run technological change that could affect harvesting decisions, allowing for state heterogeneity.

With county and year fixed effects and state-level trends, the identifying assumption is that a

county would have changed the proportion of its harvested acreage in the same way had it experienced a similar weather shock over the growing season as another county, after purging off state-level trends and country-level shocks.

ε_{it} represents the error term, which is potentially correlated between counties and across years as discussed in Auffhammer et al. (2013). The estimation accounts for potential spatial and serial correlation in the error term by clustering standard errors at both county and state-by-year levels, following Cameron, Gelbach and Miller (2011). This strategy permits arbitrary spatial correlation across counties within a state-year combination and serial correlation over years within a county. An alternative inference method using state-level clusters produces very similar standard errors (shown in Appendix).¹

3 Data

The empirical analysis combines crop production data, weather data, and complementary information related to crop prices and the Federal insurance program. The summary statistics for key variables are presented in Appendix.

3.1 Crop Production Data

County-level crop data are sourced from USDA’s QuickStats. The data contain annual records on planted and harvested acres of corn and soybeans for the lower 48 states. For corn, the data on harvested acres separately report grain and silage acres, but the data on planted acres do not distinguish between the two. The analysis in this article focuses on grain corn because it constitutes the majority of total corn acreage, and corn acreage as silage is treated in the robustness checks. Soybean acreage data are free from this issue as there is only one product type at harvest. For data completeness, only data after 1980 are used for the analysis.

¹State-level cluster robust standard errors have been used in US county-level studies including Deschênes and Greenstone (2007) and Burke and Emerick (2016). This article concentrates on the major producing region, so using state-level clusters may cause problems related to a small number of clusters (Cameron and Miller, 2015).

County-level data on irrigated acres are available in some states.² In these states, counties with irrigated acres exceeding 10% of the total acres are identified as irrigated counties and excluded from the analysis.³ Among states with no irrigated acreage data, the Western states as well as states surrounding the Mississippi Delta are removed due to their likely reliance on groundwater irrigation. To eliminate noisy information caused by counties that do not regularly grow corn and soybeans, the sample is further restricted to the counties reporting positive corn and soybean planted acres for at least 30 years within the observed 35-year period. The final sample contains 786 counties from 13 states for corn, and 1084 counties from 23 states for soybeans.

3.2 Weather Data

Historical weather data are based on the data in Schlenker and Roberts (2009), with the latest data updated to 2015. The county-level daily data from 1981 to 2015 are spatially interpolated from the high-resolution daily weather data provided by the PRISM within the cropland areas.⁴ Weather data and crop data are merged according to the unique identifier of FIPS codes.

As discussed in Section 2, summarizing relevant weather information to the yearly level requires aggregating daily temperature and precipitation over the growing season in a year. I use crop progress reports by USDA to identify the actual growing season of each year from 1981 to 2015 (USDA, 2017). For major corn and soybean states, USDA reports state-level planting and harvesting progress (as a percentage) on a weekly basis. For each state in each year, I use the dates corresponding to the median progress of planting and harvesting to define the starting and ending dates of a growing season. When unavailable, this information is imputed by using the state-specific mean dates over 1981-2015. The starting and closing dates as well as the length of the actual growing season vary across states and years (see Appendix).

²Irrigated acreage data are available for counties in Colorado, Delaware, Idaho, Kansas, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, and Wyoming for corn, and in Arkansas, Delaware, Kansas, Nebraska, and Texas for soybeans.

³This criteria has also been used in prior studies (e.g., Deschênes and Greenstone, 2007).

⁴I thank Michael Roberts and Wolfram Schlenker for making the data and relevant program codes available at <https://www.columbia.edu/~ws2162/dailyData.html>

3.3 Other Data

Additional data on crop prices and crop insurance are used for analyzing heterogeneous responses. I obtain state-level received crop prices for corn and soybeans from USDA's QuickStats. The prices are deflated using a GDP deflator. Data on crop insurance are obtained from the Risk Management Agency (RMA), USDA. The data set consists of county-level records of Federal crop insurance program enrollments from 1980, specific to crops and plan types, which allows for constructing measures of county-level participation rates for corn and soybeans, respectively.

4 Estimation and Results

In this section, I introduce specific econometric models for identifying weather effects on both harvested ratios and logarithmic yields for corn and soybeans, and present and interpret the estimation results.

4.1 Semi-parametric estimation

I start with the following semi-parametric specification to flexibly characterize the effects of growing-season climatic factors on the acreage abandonment of corn and soybeans, respectively.

$$\left(\frac{Acres^H}{Acres^P}\right)_{it} = \sum_j \theta_j TBin_{it}^j + \gamma_1 Prec + \gamma_2 Prec^2 + \delta_{1,s}t + \delta_{2,s}t^2 + \eta_t + \alpha_i + \varepsilon_{it}. \quad (4)$$

The dependent variable is the harvested ratio of a specific crop in county i in crop year t , in which $Acres^H$ and $Acres^P$ represent harvested and planted acres, respectively. By construction, the ratio is bounded between zero and one. I construct harvested ratios for grain corn and soybeans separately.⁵

The set of $TBin_{it}^j$ accounts for the crop-specific growing-season temperature distribution in

⁵Robustness checks in Appendix show that including corn silage in calculating corn harvested ratio does not qualitatively affect the results.

county i in year t . Each $TBin_{it}^j$ variable is a constructed ratio, in which the numerator is the number of days within the growing season with *temperature exposures* falling into the j th bin, and the denominator is the total number of days of the growing season. Each $TBin_{it}^j$ hence characterizes the fraction of the growing season in which a county is exposed to a specific range of temperatures. To fully utilize the information regarding within-day diurnal temperature change, the temperature exposure is constructed based on a sinusoidal interpolation between the daily maximum and minimum temperatures. Calculating the temperature exposure with only daily average temperature would have lost meaningful information on extreme heat exposures (see Appendix for more details). The following temperature bins are used: 10-13°C, 13-16°C, 16-19°C, 19-22°C, 22-25°C, 25-28°C, 28-31°C, 31-34°C, 34-37°C, and above 37°C. The selection of temperature cutoffs follows convention in the literature. I also show robustness of the results to alternative cutoffs in Appendix.

In addition to temperature variables, $Prec_{it}$ represents the cumulative precipitation over the growing season. The inclusion of its squared term captures the potential quadratic relationship as widely documented in the literature. The other terms follow the definitions in equation (3). To facilitate comparison with yield responses, the regression equation is also implemented using logarithmic yields as the dependent variable.⁶ In particular, the yields are measured over harvested acres, not planted acres, consistent with the yield response literature following Schlenker and Roberts (2009).⁷

The upper panel of Figure 2 presents the temperature effects on the harvested ratios of corn and soybeans, respectively. The markers and error bars represent point estimates and 95% confidence intervals of the estimates of θ_j , red for corn and blue for soybeans. Since the temperature variables are proportions, in this context, θ_j can be interpreted as the elasticity of the harvested ratio with respect to a marginal increase of temperature exposure within the range of the j th bin in a growing

⁶In NASS data, yields (harvested) are recorded as *NA* (i.e. missing) if the crops are not harvested. The final sample contains a single observation that records the yield (harvested) as zero: the 2001 corn yield in Delta county, Michigan. All the recorded yields are added by one before taking the logarithmic transformation.

⁷The main results in Schlenker and Roberts (2009) are based on yields measured over harvested acres. In the extensive appendix, they show that using yields over planted acres will produce similar results in terms of the nonlinear yield response to temperature. However, they do not further explore the nuances between the two sets of estimates.

season, with the reference being exposure to temperatures below 10°C.

Additional heat accumulation just above 10°C strongly increases corn harvested ratio. A one percentage increase of exposure to 10-13°C and 13-16°C within the growing season will increase corn harvested ratio by 0.33 and 0.28 percentage points, respectively. However, there is no evidence for this low-range temperature effect on soybean harvested ratio. Both crops are positively affected by medium-range temperatures. In particular, a one percentage proportional increase of temperature exposure to 25-28°C is found to significantly increase corn harvested ratio by 0.38 percentage points; and a one percentage proportional increase of temperature exposure to 22-25°C is found to significantly increase soybean harvested ratio by 0.14 percentage points.

Both crops are significantly affected by exposures to extreme heat, with a comparable magnitude of the effects. The only exception is the positive estimate of 34-37°C for corn, but it is not statistically significant at the conventional level. When the exposure to temperatures beyond 37°C increases by one percentage, the negative effects on harvested ratios amount to 3.33 and 3.09 percentage points for corn and soybeans, respectively. It is worth noting that the occurrence of temperature exposure above 37°C is not negligible after taking account for the diurnal variation in daily temperature. For example, some counties in Kansas and Nebraska have experienced temperature exposure over 37°C for more than 3% of a corn growing season in certain years.

For comparison, the lower panel of Figure 2 plots the temperature effects on corn and soybean yields, respectively.⁸ Since the dependent variable is in logarithm, the estimated coefficients can also be interpreted as elasticities. Qualitatively similar to the patterns of harvested ratio estimates, the patterns of yield estimates indicate that yields are positively affected by moderate heat accumulation, but negatively affected by exposures to extreme heat, consistent with findings in the literature (e.g., Schlenker and Roberts, 2009).

⁸See numerical representation of the results in Appendix.

Figure 2: Semi-parametric Estimation of Temperature Effects on Harvested Ratios and Logarithmic Yields

Note: The markers and error bars represent the point estimates and the 95% level confidence intervals of the elasticities for corn and soybeans, as labeled in the legend. Numerical results are shown in Appendix.

Temperature accumulation between 22-28°C appears to be most beneficial to corn and soybean yields. A one percentage proportional increase of temperature exposure to 22-25°C is associated with a 1.05 and 1.71 percentage points increase in the yields of corn and soybeans, respectively; and the corresponding effects of temperature exposure to 25-28°C are 1.20 and 0.93 percentage points, respectively. Heat exposure beyond 31°C is detected to be significantly damaging to crop yields, with a one percentage proportional increase of exposure leading to more than 2 percentage points reduction in yields. The yield losses under temperatures higher than 37°C are particularly high. When the proportion of temperature exposure beyond 37°C increases by one percentage, the associated yield losses amount to 21.63 and 7.81 percentage points for corn and soybeans, respectively.

The upper panel of Figure 3 plots the marginal effects of an additional 100mm cumulative precipitation on corn and soybean harvested ratios over the support of observed growing-season precipitations. More precipitation positively affects corn harvested ratio when cumulative precipitation has been low, but the effect reverses when cumulative precipitation becomes high. The turning point is around 500mm. The magnitude of the effect is roughly in between plus and minus 2 percentage points for an additional 100mm precipitation. In contrast, soybean harvested ratio is only found to be negatively affected by more precipitation, despite the magnitude of the effect is smaller than that of corn for high-range precipitations. For example, when evaluated at 1000mm, the reduction in harvested ratio induced by an additional 100mm precipitation is 1.44 percentage points for corn and 1.02 percentage points for soybeans.

In contrast to the harvested ratio estimates, the yield estimates of precipitation effects are highly similar for corn and soybeans, as shown in the lower panel of Figure 3. More rainfall increases yields in dry areas but decreases yields in wet areas, with the turning point around 600mm. The magnitude of yield impacts ranges from plus and minus 15 percentage points over the precipitation support, relatively higher than the impacts on harvested ratios.

Marginal Effects on Harvested Ratios

Marginal Effects on Logarithmic Yields

Figure 3: Marginal Effects of Cumulative Precipitation

Note: The solid lines represent the point estimates of marginal effects, and the shallow bands represent 95% level confidence intervals. The marginal effects are calculated based on precipitation estimates of equation (4), over the support of observed precipitations. The confidence intervals are constructed using the Delta's method based on two-way clustered standard errors.

As documented above, the magnitude of both temperature and precipitation effects is generally larger on yields than on harvested ratios, showing that crop yield is still the first-order responsive margin. However, comparing differences between harvested ratio and yield estimates across corn and soybeans can provide some key insights on understanding the behavioral responses of the farmers.

The nonlinearity in temperature response differs between harvested ratios and crop yields. The significant negative effects appear at a relatively lower temperature range on yields than on harvested ratios. This finding suggests that heat-induced yield loss does not necessarily lead to harvest abandonment as long as the growers still find harvesting to be profitable. Farmers will forgo harvesting due to extremely high temperatures only if the yield loss is so high that harvesting can no longer justify its opportunity cost.

Moreover, the relative impacts on corn and soybean harvested ratios do not mirror the relative impacts on their yields. The accumulation of low-range temperature exposure does not significantly affect corn and soybean yields, but it is found to significantly increase the harvested ratio of corn. In contrast, although high-range temperature exposure has a much larger impact on the yield of corn than soybeans, its impacts on the harvested ratios of the two crops are comparable. Besides, more precipitation in dry areas improves yields for both crops, but it does not significantly affect the harvested ratio of soybeans.

In general, the harvest ratio of corn is more responsive when favorable weather conditions are met, but less responsive to unfavorable weather conditions. One explanation rests on the difference in per-acre revenues of these two crops. Figure 4 shows that the per acre revenue for corn has been consistently higher than soybeans by 1.3-1.6 times during most of the time since 1980. Meanwhile, as suggested by the statistics from agricultural extension departments, operating costs are generally comparable for harvesting corn and soybeans.⁹ All else equal, corn growers, as compared with soybean growers, are more incentivized to adjust their harvest according to weather as the per-acre revenue realized from harvesting corn is relatively higher.

⁹See *Purdue Crop Cost and Return Guide* as an example.

Figure 4: National Average Per Acre Revenues of Corn and Soybeans: 1980-2015

Note: Per acre revenues are calculated by multiplying national average yields and received nominal prices, based on annual survey data from USDA.

4.2 Degree Days Estimation

In the literature on estimating the relationship between agricultural outcomes and climatic factors, it has become a popular choice to use degree days variables for measuring the nonlinear temperature effects (e.g., Schlenker, Hanemann and Fisher, 2005; Burke and Emerick, 2016; Miao, Khanna and Huang, 2016). The growing degree days (GDD) accounts for heat accumulation beneficial to crop growth, and the heat degree days (HDD) captures heat accumulation of high temperature that potentially stunts crop growth. The estimation is in the fashion of the following equation.

$$y_{it} = \beta_1 GDD_{it} + \beta_2 HDD_{it} + \gamma_1 Prec + \gamma_2 Prec^2 + \delta_{1,s}t + \delta_{2,s}t^2 + \eta_t + \alpha_i + \varepsilon_{it}, \quad (5)$$

where y_{it} represents the agricultural outcome in county i in year t . GDD_{it} and HDD_{it} represents growing and heat degree days, respectively. The other terms follow the definitions in equation (4).

For corn and soybeans, the temperature cutoff separating GDD and HDD is normally around 29-30°C as identified in the literature (Schlenker and Roberts, 2009; Burke and Emerick, 2016).

One thing to note is that using HDD for estimating the damaging effect of high temperature implicitly assumes the effect is linear-in-degrees for temperatures above the critical threshold. For instance, when using 29°C as the threshold, the marginal effect of an additional day of 35°C is equivalent to that of two additional days of 32°C. However, as illustrated in Figure 2, exposures to extreme heat is particularly damaging, both in terms of yields and harvested ratios. Therefore, the coefficient of HDD may only capture the average effect of heat accumulation beyond the critical temperature threshold, and could mask further nonlinearity at a higher range of temperature exposure.

To test if using HDD is sufficient for characterizing the effect of extreme heat exposures on harvested ratios, I conduct the following estimation.

$$\left(\frac{Acres^H}{Acres^P}\right)_{it} = \beta_1 GDD_{it} + \beta_2 HDD_{it} + \gamma_1 Prec + \gamma_2 Prec^2 + \theta EHD_{it} + \delta_{1,s}t + \delta_{2,s}t^2 + \eta_t + \alpha_i + \varepsilon_{it}. \quad (6)$$

GDD and HDD accumulate growing-season temperature exposures within 10-29°C and above 29°C, respectively.¹⁰ When constructing the degree days, a sinusoidal interpolation is made between the daily maximum and minimum temperature to bring in diurnal variation in daily temperature. Throughout this article, GDD is scaled at 100°C for illustration purpose.

Compared with equation (5), the additional variable EHD_{it} represents the number of extreme hot days county i has experienced in the growing season of year t . I define extreme hot days as days with daily maximum temperature higher than a certain threshold. In the United States, 100°F (about 38°C) is normally considered as particularly hot.¹¹ I hence use 38°C as the cutoff for classifying extreme hot days, and also report estimation results using alternative cutoffs varying from 37-40°C. If using HDD is sufficient for capturing the damaging effect of extremely high temperature, the estimates of θ should be statistically insignificant. For comparison, I also report

¹⁰I report results using 30°C as the critical temperature cutoff in Appendix.

¹¹The 100°F benchmark has been frequently referred to in media headlines related to heat waves. Recent examples include “Temperatures near 100 degrees across Northeast as heat wave blazes on” (July 1, 2018) and “Heat wave continues in eastern US as millions deal with heat index over 100 degrees” (August 28, 2018) on ABC News.

estimation results using yields as the dependent variable.

Tables 1 and 2 report estimation results under degree-days specifications for corn and soybeans, respectively. In each table, the upper panel presents harvested ratio estimates, and the lower panel presents yield estimates. As a reference, column (1) shows the result of regressions without including the number of extreme hot days. Columns (2)-(5) report results with extreme hot days defined using 37°C, 38°C, 39°C, and 40°C, respectively.

For corn, based on the estimates in column (1) of Table 1, a one-hundred degrees increase in GDD increases the harvested ratio and yields by 0.72% and 3.42%, respectively; and a degree increase in HDD decreases the harvested ratio and yields by 0.07% and 0.71%, respectively. The estimated effects of precipitation are very similar to those obtained from the semi-parametric regressions (see Appendix).

As shown in columns (2)-(5) in Table 1, the estimated coefficients of extreme hot days are negative and mostly statistically significant, except for that in column (2) of panel A. Adding extreme hot days slightly attenuates the estimated effects of HDD, because the effects of the highest temperature exposure have been captured in the EHD coefficients. Focusing on the preferred estimates in column (3), one more extreme hot day, i.e., a day with maximum temperature above 38°C, is associated with a 0.36 percentage point reduction in corn harvested ratio, and a 2.50 percent corn yield loss. When extreme hot days are defined using a higher temperature threshold, the magnitude of the EHD coefficients becomes larger.

For soybeans, as shown in column (1) of Table 2, a one-hundred degrees increase in GDD increases harvested ratio and yields by 0.40% and 3.25%, respectively; while a degree increase in HDD decreases them by 0.09% and 0.62%, respectively. Precipitation effects are in line with the semi-parametric estimates (see Appendix). However, columns (2)-(5) show that, conditional on HDD effects, extreme hot days only affect the harvested ratio, not yields. Comparing among the harvested ratio estimates, the magnitudes of HDD estimates in columns (2)-(5) are smaller than that in column (1), as the inclusion of extreme hot days attenuates the HDD coefficient. Based on the preferred estimates in column (3) of Table 2, one more extreme hot day is associated with a

0.48 percentage point reduction in the harvested ratio of soybeans. As the temperature threshold for defining extreme hot days becomes higher, the estimated magnitude also becomes larger.

These results suggest the importance of considering extreme hot days in addition to using HDD in estimating the relationship between climatic factors and agricultural outcomes. The only case where adding extreme hot days does not provide additional information is the estimation of soybean yield equation. As suggested in Figure 2, soybean yield losses associated with high temperature exposures is reasonably linear-in-degrees.

Although the variable definition of extreme hot days is only related to temperature, I interpret its effects as the impacts of the coupled heat and water stress. Based on a document by the World Meteorological Organization (WMO), the lower bound of daily precipitation for defining *light rain*, the first rainfall category, is 5mm (WMO, 2015). In my sample, for days with maximum temperatures above 38°C, more than 88% of the days receive less than 1mm precipitation, and more than 97% of the days receive less than 5mm precipitation. As documented in the scientific literature, the coupled heat and water stress is highly detrimental to crop growth (e.g., Jin et al., 2017), supporting my finding regarding the EHD effects.

The preferred estimates of corn and soybeans under the degree-days specification also support the findings of semi-parametric estimations. The yield estimates of GDD and HDD are very similar for corn and soybeans, consistent with the semi-parametric yield estimates of temperature bins below 37°C. In contrast to the impacts on yields, GDD has larger effect on the harvested ratio of corn than soybeans, in line with semi-parametric estimates of harvested ratios at low-range temperature bins. The estimates of extreme hot days provide information in parallel to those of the highest temperature bin in the semi-parametric regressions. When exposing to extremely high level of heat, corn and soybeans respond similarly in terms of their harvested ratios, while corn tends to be more responsive in terms of yields.

Table 1: Corn Harvested Ratio and Yield Responses to Climatic Factors

		Extreme hot days as daily max. temp.			
		>37°C	>38°C	>39°C	>40°C
	(1)	(2)	(3)	(4)	(5)
<i>A. Harvested ratio estimates:</i>					
GDD	0.0072*** (0.0021)	0.0070** (0.0022)	0.0068** (0.0022)	0.0070** (0.0021)	0.0073*** (0.0021)
HDD	-0.0007*** (0.0002)	-0.0006*** (0.0002)	-0.0005*** (0.0001)	-0.0004** (0.0001)	-0.0005*** (0.0001)
Precipitation	0.0169** (0.0056)	0.0171** (0.0057)	0.0176** (0.0057)	0.0179** (0.0057)	0.0176** (0.0057)
Precipitation, squared	-0.0015** (0.0005)	-0.0015** (0.0005)	-0.0015** (0.0005)	-0.0015** (0.0005)	-0.0015** (0.0005)
Extreme hot days		-0.0007 (0.0012)	-0.0036* (0.0017)	-0.0091* (0.0035)	-0.0233* (0.0094)
<i>B. Log yield estimates:</i>					
GDD	0.0342*** (0.0072)	0.0308*** (0.0070)	0.0310*** (0.0071)	0.0333*** (0.0072)	0.0343*** (0.0072)
HDD	-0.0071*** (0.0006)	-0.0057*** (0.0006)	-0.0055*** (0.0005)	-0.0059*** (0.0005)	-0.0066*** (0.0005)
Precipitation	0.1146*** (0.0235)	0.1173*** (0.0229)	0.1192*** (0.0226)	0.1192*** (0.0228)	0.1163*** (0.0232)
Precipitation, squared	-0.0102*** (0.0021)	-0.0102*** (0.0020)	-0.0103*** (0.0020)	-0.0103*** (0.0020)	-0.0102*** (0.0020)
Extreme hot days		-0.0121** (0.0039)	-0.0250*** (0.0057)	-0.0426*** (0.0096)	-0.0580** (0.0192)
Observations	27,018	27,018	27,018	27,018	27,018

Note: All regressions control for county fixed effects, year fixed effects, and state-level quadratic time trends. Standard errors (in parentheses) are two-way clustered by county and year. The units of measure for growing degree days (GDD), heat degree days (HDD), precipitation, and hot and dry days are 100°C, °C, mm, and number of days. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Soybean Harvested Ratio and Yield Responses to Climatic Factors

		Extreme hot days as daily max. temp.			
		>37°C	>38°C	>39°C	>40°C
	(1)	(2)	(3)	(4)	(5)
<i>A. Harvested ratio estimates:</i>					
GDD	0.0040*** (0.0009)	0.0030*** (0.0008)	0.0030*** (0.0008)	0.0031*** (0.0008)	0.0033*** (0.0008)
HDD	-0.0009*** (0.0001)	-0.0004*** (0.0001)	-0.0004*** (0.0001)	-0.0005*** (0.0001)	-0.0006*** (0.0001)
Precipitation	0.0026 (0.0038)	0.0045 (0.0038)	0.0048 (0.0038)	0.0050 (0.0038)	0.0043 (0.0037)
Precipitation, squared	-0.0007 (0.0004)	-0.0008 (0.0004)	-0.0008 (0.0004)	-0.0008 (0.0004)	-0.0008 (0.0004)
Extreme hot days		-0.0031*** (0.0007)	-0.0048*** (0.0010)	-0.0081*** (0.0016)	-0.0140*** (0.0027)
<i>B. Log yield estimates:</i>					
GDD	0.0325*** (0.0051)	0.0323*** (0.0050)	0.0323*** (0.0051)	0.0324*** (0.0051)	0.0325*** (0.0051)
HDD	-0.0062*** (0.0003)	-0.0061*** (0.0004)	-0.0061*** (0.0004)	-0.0062*** (0.0003)	-0.0062*** (0.0003)
Precipitation	0.1082*** (0.0118)	0.1086*** (0.0119)	0.1087*** (0.0119)	0.1085*** (0.0118)	0.1081*** (0.0119)
Precipitation, squared	-0.0090*** (0.0011)	-0.0090*** (0.0011)	-0.0090*** (0.0011)	-0.0090*** (0.0011)	-0.0090*** (0.0011)
Extreme hot days		-0.0006 (0.0018)	-0.0010 (0.0024)	-0.0009 (0.0036)	0.0009 (0.0065)
Observations	37,084	37,084	37,084	37,084	37,084

Note: All regressions control for county fixed effects, year fixed effects, and state-level quadratic time trends. Standard errors (in parentheses) are two-way clustered by county and year. The units of measure for growing degree days (GDD), heat degree days (HDD), precipitation, and Extreme hot days are 100°C, °C, mm, and number of days. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.3 Response Heterogeneity

Building on the preferred degree-days specification, this section further explores the heterogeneity in harvested ratio responses to weather shocks, relating to market conditions and the Federal crop insurance program.

4.3.1 Crop Price Regimes

Weather shocks may induce different behavioral responses when market conditions are different. The stylized theoretical model implies that, given all else equal, the unharvested proportion of land will weakly decrease under an weather-induced left shift of the yield distribution if the output price is higher. This implication is intuitive given that farmer may tend to save more lower-yield land if the marginal profit is relatively higher due to a higher output price.

To test this hypothesis empirically, I revise equation (6) to incorporate response heterogeneity with respect to different crop prices. The regression equation is written as

$$\left(\frac{Acres^H}{Acres^P}\right)_{it} = \mathbf{W}'_{it}\beta + (Price_{st} \times \mathbf{W}'_{it})\gamma + \delta_{1,st} + \delta_{2,st}t^2 + \eta_t + \alpha_i + \varepsilon_{it}. \quad (7)$$

The outcome of most interest is the harvested ratio, but I also implement this regression on crop yields as a comparison. In addition to terms defined before, for simplicity, I use $\mathbf{W}_{it}$ to denote a vector holding weather variables including GDD_{it} , EDD_{it} , $Prec_{it}$, $Prec_{it}^2$, and EHD_{it} . $Price_{st}$ is a continuous variable of price deviation, constructed by subtracting the median received crop price of the entire sample from the state-level received crop price in year t . The assumption for using current year price is that farmers' price expectation is reasonably close to the final received price at the time of harvest. All prices are deflated by US GDP using 2010 as the reference year. The calculated median prices are 3.52 and 8.91 in 2010 US dollars for corn and soybeans, respectively.

In this specification, parameters held in β are interpreted as marginal effects of weather variables evaluated at the median price level. Parameters held in γ thus represent the additional effects of weather when the real received price is one-dollar per bushel higher than the median price. One

may concern that crop prices are correlated with weather outcomes in the US corn belt so that the interpretation of price-related response heterogeneity is confounded. I argue that this is not a critical issue in the context of this article. First, given the global integration of the commodity market, crop prices are determined by many factors including demand-side shocks, storage adjustments, and weather-induced supply shocks in other producing countries. Moreover, the variation in weather variables is at county-level and thus is more granular than variation in the state-level price information.¹² In addition, the effect of a US country-wide weather shock will also likely be absorbed by year fixed effects.

Table 3 presents the estimation results. Columns (1) and (2) present harvested ratio estimates for corn and soybeans, respectively; and columns (3) and (4) present yield estimates. The coefficients of GDD, HDD, precipitation and its squared term, as well as EHD are in line with those preferred estimates in Tables 1 and 2. It is worth pointing out that the coefficients in Table 3 represent partial weather effects evaluated at the median real price, while those in Tables 1 and 2 represent average partial effects for the full sample. This difference in interpretation also explains the slight difference between the two sets of the estimates.

Column (1) in Table 3 shows that the GDD effect on the harvested ratio of corn becomes 0.15 percentage-point smaller if the real received corn price is one dollar higher than the median price level. Interpreting this coefficient in the context of a negative weather shock, it shows that the harvested ratio of corn is less affected by insufficient GDD if corn price is relatively high. This interpretation is consistent with rational behaviors of farmers as they are less willing to forgo harvesting on the marginal land when per-acre revenue is higher, *ceteris paribus*. Column (2) in Table 3 suggests that similar behaviors also occur on soybean farmers' response to HDD and extreme hot days. The decreases in soybean harvested ratio induced by one more degree of HDD and one more extreme hot day are mitigated by 0.01 and 0.08 percentage points, respectively, if the received price is one dollar higher than the median price in real terms.

¹²The simple correlations between the variable *Price* and GDD, HDD, precipitation, and extreme hot days are 0.10, 0.30, -0.14, 0.27 for corn, and 0.02, 0.20, -0.16, 0.18 for soybeans, respectively.

Table 3: Response Heterogeneity over Different Crop Price Regimes

	Harvested Ratio		Log Yield	
	Corn (1)	Soybean (2)	Corn (3)	Soybean (4)
GDD	0.0056 (0.0037)	0.0033*** (0.0009)	0.0295 (0.0154)	0.0324** (0.0106)
× <i>Price</i>	-0.0015* (0.0007)	-0.0003 (0.0002)	-0.0058* (0.0026)	-0.0015 (0.0017)
HDD	-0.0004 (0.0002)	-0.0004*** (0.0001)	-0.0059*** (0.0010)	-0.0063*** (0.0006)
× <i>Price</i>	0.0000 (0.0001)	0.0001* (0.0000)	0.0007 (0.0004)	0.0003 (0.0002)
Precipitation	0.0179*** (0.0048)	0.0046 (0.0041)	0.1242*** (0.0276)	0.1112*** (0.0160)
× <i>Price</i>	-0.0006 (0.0035)	0.0009 (0.0010)	-0.0184 (0.0172)	-0.0056 (0.0052)
Precipitation, squared	-0.0016*** (0.0004)	-0.0008 (0.0005)	-0.0107*** (0.0023)	-0.0092*** (0.0014)
× <i>Price</i>	0.0001 (0.0003)	-0.0001 (0.0001)	0.0010 (0.0016)	0.0005 (0.0004)
Extreme hot days	-0.0056 (0.0047)	-0.0068*** (0.0010)	-0.0140 (0.0108)	0.0003 (0.0041)
× <i>Price</i>	0.0011 (0.0017)	0.0008** (0.0003)	-0.0089 (0.0044)	-0.0018 (0.0013)
Observations	27,018	37,084	27,018	37,084

Note: All regressions control for county fixed effects, year fixed effects, and state-level quadratic time trends. Standard errors (in parentheses) are two-way clustered by county and year. The units of measure for growing degree days (GDD), heat degree days (HDD), precipitation, and extreme hot days are 100°C, °C, mm, and number of days. Extreme hot days are days with daily maximum temperature above 38°C. *Price* is the per-bushel real crop price deviation from the median real price of the sample, measured in 2010 US dollar. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Columns (3) and (4) in Table 3 report price-related response heterogeneity in corn and soybean yields, respectively. Qualitatively similar to corn harvested ratio, corn yields respond to GDD to a lesser extent when corn price is high. In the context of receiving insufficient GDD, farmers may put in more effort (including use more fertilizer) to maintain yields in a higher price year. In contrast with corn, there is no evidence of price-related response heterogeneity on soybean yields.

The lower per-acre revenue of soybeans may explain that soybean farmers are less incentivized to exert more efforts on maintaining yields when facing unfavorable weather conditions.

4.3.2 Federal Crop Insurance Participation Rates

Specific institutional arrangements may also give rise to response heterogeneity. An important institution that may affect the relationship between agricultural outcomes and climatic factors is the Federal crop insurance program. Policy makers have made huge efforts to minimize the chance for adverse selection and moral hazard. In particular, for most weather-related risks, the insurance payment is not contingent on whether the farmer chooses to harvest or not. However, there remain channels that could exacerbate the impacts of weather on crop abandonment. The heavy subsidy on insurance premium may have lowered the intensity of input use on the intensive margin and induced expansion to less suitable lands on the extensive margin (Smith and Goodwin, 2013; Yu, Smith and Sumner, 2017). Both channels may skew the yield distribution, potentially resulting in higher vulnerability to weather shocks.

To infer if the participation of the Federal crop insurance is associated with heterogeneous responses in harvested ratios to weather shocks, I implement the following regression equation,

$$\left(\frac{Acres^H}{Acres^P} \right)_{it} = \mathbf{W}'_{it}\beta + (Insured_{it} \times \mathbf{W}'_{it})\gamma + \delta_{1,s}t + \delta_{2,s}t^2 + \eta_t + \alpha_i + \varepsilon_{it}. \quad (8)$$

For comparison, I also implement this regression using yields as the dependent variable. In addition to terms defined in equation (7), $Insured_{it}$ is a continuous variable representing the participation rate of Federal crop insurance program at the county-year level. The variable is constructed as follows. For each county in each year, the insured acres of corn and soybeans are separately obtained by aggregating all plan types for the insured quantity measured in acreage. The county-level insured rates are then calculated from dividing the insured acres by the planted acres. I then difference these calculated rates with the year-specific median levels of insured rates, so that the variable $Insured_{it}$ measures the county-level participation intensity deviated from the median level

of the current year. By construction, the parameter vector β captures weather effects evaluated at the median level of insurance participation in a year.

This complexity in constructing the insured rate arises from the peculiarity of the program. The Federal insurance program has undergone substantial changes over the sample period, and the overall participation of the program has gone up steadily. Pooling variation of insurance participation across years will lead to potentially biased estimate of γ , because the levels of insured rates across years are not fully comparable. By differencing county-level insured rate with year-specific median rate, I will only compare the more insured with the less insured in any given year, which is free of the cross-year comparability issue caused by changes of the program.

Table 4 columns (1)-(2) present harvested ratio estimates and columns (3)-(4) present yield estimates for corn and soybeans, respectively. The estimates associated with GDD, HDD, precipitation and its squared term, and EHD are very similar to the preferred estimates in Tables 1 and 2. Among these results, response heterogeneity related to insurance participation is only found to be significant on the effect of extreme hot days on corn harvested ratio. For counties with insured rates 10 percentage point higher than the year-specific median, the additional reduction in corn harvested ratios associated with one more extreme hot day is about 0.16 percentage point. This result partly reflects the increased crop vulnerability associated with higher participation of subsidized crop insurance, as the abandoned corn acres (likely with the lowest yields) become higher under the coupled heat and water stress.

My yield estimates are somewhat different from those in Annan and Schlenker (2015), which is likely driven by the difference in variation of insured rates utilized for exploring the heterogeneity. While Annan and Schlenker (2015) pool variation across years, I only compare the more and the less insured counties within a year for better comparability.

Table 4: Response Heterogeneity over Different Federal Insurance Participation Rates

	Harvested Ratio		Log Yield	
	Corn (1)	Soybean (2)	Corn (3)	Soybean (4)
GDD	0.0068 (0.0036)	0.0030** (0.0009)	0.0308* (0.0136)	0.0310** (0.0090)
× <i>Insured</i>	0.0111 (0.0091)	0.0018 (0.0016)	0.0328 (0.0222)	0.0286 (0.0159)
HDD	-0.0005* (0.0002)	-0.0004** (0.0001)	-0.0056*** (0.0009)	-0.0062*** (0.0005)
× <i>Insured</i>	-0.0001 (0.0007)	0.0000 (0.0002)	-0.0029 (0.0019)	-0.0014 (0.0010)
Precipitation	0.0188*** (0.0052)	0.0050 (0.0042)	0.1159** (0.0343)	0.1093*** (0.0158)
× <i>Insured</i>	-0.0488 (0.0444)	-0.0097 (0.0065)	-0.1069 (0.0920)	-0.1114 (0.0698)
Precipitation, squared	-0.0017** (0.0005)	-0.0008 (0.0005)	-0.0101** (0.0028)	-0.0091*** (0.0014)
× <i>Insured</i>	0.0038 (0.0037)	0.0008 (0.0005)	0.0055 (0.0064)	0.0059 (0.0050)
Extreme hot days	-0.0033 (0.0018)	-0.0046** (0.0015)	-0.0236* (0.0101)	-0.0006 (0.0033)
× <i>Insured</i>	-0.0157* (0.0071)	0.0030 (0.0020)	-0.0187 (0.0154)	0.0031 (0.0069)
Observations	27,018	37,084	27,018	37,084

Note: All regressions control for county fixed effects, year fixed effects, and state-level quadratic time trends. Standard errors (in parentheses) are two-way clustered by county and year. The units of measure for growing degree days (GDD), heat degree days (HDD), precipitation, and extreme hot days are 100°C, °C, mm, and number of days. Extreme hot days are days with daily maximum temperature above 38°C. *Insured* is crop-specific Federal insurance participation rate deviated from the year-specific median rate, measured in percentage. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5 Concluding Remarks

When bad weather strikes, farmers may abandon their planted crops if the revenues to be collected from the lowered yields could not justify the opportunity cost of harvesting. Although there have been extensive measurements of weather impacts on crop yields, the quantitative relationship between weather shocks and the behavioral outcome of harvesting has not received much attention. This article starts with a stylized conceptual model to illustrate the mechanism of weather-induced crop abandonment, and empirically examines how climatic factors within a growing season affect corn and soybean harvests using US county-level data.

I find both temperature and precipitation significantly affect the county-level harvested ratios of corn and soybeans in a nonlinear fashion. Moderate heat and precipitation increase the harvested ratios, while excessive heat and precipitation encourage crop abandonment. Comparing yield and harvested ratio estimates helps infer the rationale of farmers' behaviors. Acknowledging that yield responses still constitute the first-order effect, responses in harvested ratios show a tendency against the yield response especially if crop revenue is high. I further explore the heterogeneous responses related to different crop price regimes and participation rates of the Federal crop insurance. The results are consistent with the rationale illustrated by the conceptual model.

The findings in this article directly speaks to the vulnerability of agriculture under a changing climate. In developed countries like the United States, more seed breeding efforts have been devoted for chasing higher yields than maintaining lower risks, given the predominance of subsidized crop insurance. As extreme weather events become more frequently, the weather-induced crop abandonment will disproportionately increase, potentially causing substantial social welfare loss. On the other hand, in those developing countries with even higher climatic risks and lower adaptability, this weather-induced crop abandonment could be much larger when bad weather strikes. These implications highlight the importance in developing risk-reducing tools, including new varieties of seeds and low-cost yield-maintaining technologies, as they are critical for agricultural adaptation to future climate change.

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