Hot Dry Spells and Extreme Rain in the U.S. Midwest Raise New Crop Prices

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Abstract

The U.S. Midwest produces about a third of global corn and soybeans, two of the most important crops for humanity. We explore how changing weather patterns and extreme weather in the U.S. Midwest have impacted crop valuation at the Chicago Mercantile Exchange, which serves as global reference for these crops. We find that regional summer rain increased between 1971 and 2019 while extreme temperatures remained stable on average. We also find that hot dry spells and excessive rain in the summers of 1971-2019 contributed to contemporaneous price increases for growing crops. Predicted market returns in response to weather shocks were in extreme cases comparable to an economically significant 10% in magnitude. The market impact of excessively wet spells gained strength in later decades, in coincidence with increasing rain. We empirically confirm that the nonlinear price response to precipitation and temperature was compatible with the impact of weather on terminal yields. Our results suggest that extreme weather and changing weather patterns in the U.S. Midwest had a significant influence in the valuation of corn and soybeans.

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1. Introduction

Corn and soybeans are two of the most important sources of calories for humanity and for animal feed. The U.S. Midwest has produced in recent decades about 33% of global corn and 34% of global soybeans [Wang et al., 2020]. In the context of changing weather patterns, we explore the impact that summer weather in the U.S. Midwest had on corn and soybean prices between 1971 and 2019. We focus on futures prices at the Chicago Mercantile Exchange (CME), which serve as reference for global trade and that reflect expected supply and demand for the new crop that grows during the summer and is harvested in the fall.

Climate variability has explained about a third of observed global yield variability in recent decades and more than 40% in some areas of the U.S. Midwest [Ray et al., 2015]. Earlier work has found that high temperatures, drought and excessive rain are all detrimental to corn and soybean yields [Tannura et al., 2008, Schlenker and Roberts, 2009, Miao et al., 2016, Lesk et al., 2016, Vogel et al., 2019]. Low soil moisture during the middle of the growing season, which depends on precipitation, evapotranspiration driven by temperature and local soil characteristics, has recently been shown to lower corn and soybean yields [Ortiz-Bobea et al., 2019, Rigden et al., 2020, Proctor et al., 2022]. Early work by Rosenzweig et al. [2002] projected a doubling of corn output losses by 2030 due to increased precipitation induced by climate change in the U.S. More recent work has found a strongly negative average impact of global warming on crop yields and agricultural productivity [Lobell et al., 2011, Hsiang et al., 2017, Zhao et al., 2017, Jägermeyr et al., 2021, Ortiz-Bobea et al., 2021] that is, however, heterogeneous across space.

Negative climate effects on yields are already apparent in Europe [Moore and Lobell, 2015, Brás et al., 2021]. The U.S. Midwest is expected to suffer a decrease in agricultural productivity if summer temperatures over 30 degrees Celsius increase in frequency [Schlenker and Roberts, 2009, Lobell et al., 2013]. However, this negative effect has apparently not materialized yet. On the contrary, Mueller et al. [2016], Tollenaar et al. [2017], Butler et al. [2018] and Rizzo et al. [2022] found that the U.S. Midwest has experienced increasing average yields caused in part by a higher frequency of moderate temperatures that allow earlier planting, a decrease in the incidence of extreme temperatures and higher precipitation during the summer. However, higher corn yields have become more sensitive to droughts [Lobell et al., 2020], thus widening the output gap across growing conditions. Weather extremes have also increased spatial yield correlations [Tack and Holt, 2016].

Unlike work on yields, direct estimates for the impact of weather shocks on crop prices are less common. Most closely related to our work is [Letta et al., 2022] who found that pre-harvest weather shocks in India during 2004-2017 that were expected to damage crops, were incorporated in local market prices in anticipation of reduced supply. Earlier work includes [Keppenne, 1995, Ubilava, 2017] focusing on the impact of more slowly moving ENSO signals on the level of soybean and wheat prices. Work has also explored the effect of the ENSO oscillation on corn and soybean price volatility [Peri, 2017, Su et al., 2022], and the effect of global temperature anomalies since 1999 on corn and soybeans among other commodities [Makkonen et al., 2021]. Brown and Kshirsagar [2015] and Hatzenbuehler et al. [2020] found that local food prices in developing markets, mostly in Africa, are sensitive to

local weather shocks proxied by variations in local vegetation indices. In this paper we focus on the market impact of changing weather patterns and high frequency extreme events during the 1971-2019 corn and soybean growing seasons in the U.S. Midwest.

Market prices differ from yields in two fundamental aspects. First, there is no meaningful spatial heterogeneity in prices. The widely followed prices of corn and soybeans at the CME reflect global demand and aggregate expected supply including that from all of the U.S. Midwest, therefore concealing fixed spatial variability in soil quality. Second, unlike yields, which are measured once a year, crop prices are available at any time during the growing season and dynamically incorporate the most recent information on expected output at future harvest. Hence, we choose to focus on the contemporaneous response of CME market prices to regional weather shocks. These are first in the causal chain from weather to soil moisture and later yields. In addition, timely rain and temperature information has been widely followed by farmers and other market participants and has been historically available for many decades. Informed by the nonlinear relationship between weather and physical output, we study the effect that U.S. Midwest weather shocks during June, July and August from 1971 to 2019 had on contemporaneous corn and soybean percentage CME price changes, also called returns. The region we consider comprises all of twelve states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin. Our data sources for daily rain and temperature measures are 1,311 weather stations (Methods). Our main findings are summarized as follows. First, we provide empirical evidence of a strong increase

in summer precipitation in the U.S. Midwest over the 1971-2019 period. Then, we show that the negative response of yields to extreme heat and insufficient rain, or to excessive precipitation, was mirrored by an economically significant and previously undocumented nonlinear market response to these weather events. Finally, we find that the market response to excessive precipitation gained strength in recent decades, in line with shifting weather patterns and yields' responses to rain.

2. Results

2.1. Summer rain increased in the U.S. Midwest while extreme temperatures remained stable

We investigate the potential existence of a statistically and agronomically significant shift in the distribution of daily rain and temperature variables in the U.S. Midwest between 1971 and 2019. While climate change induced by global warming is a global phenomenon, its expression is highly heterogeneous across countries and regions. Our approach to assess potential changes in weather patterns in the U.S. Midwest is agnostic and data driven. Because crop prices at the CME respond to aggregate supply including that from the entire U.S. Midwest, it is relevant to analyze the behavior of rain and temperature time series constructed as spatial averages over the entire region.[1] In addition, we complement our regional analysis with local tests to uncover potential spatial heterogeneity.

Weather data sources are described in (Methods, section *4.1.*). Table A.1 (Extended Data) presents summary statistics for weather variables at daily and monthly fre-

[1] Alternative averaging schemes, including weighting weather variables in each state by state share of crop production, led to very similar results to those presented in this paper.

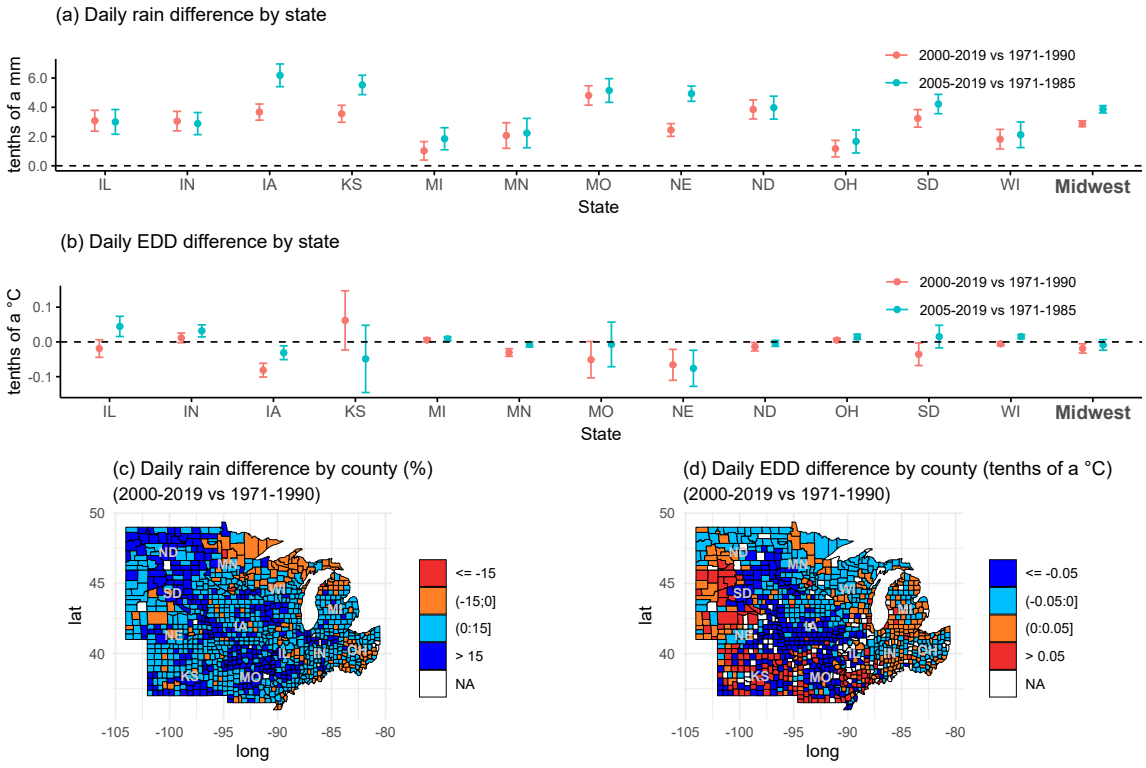


Figure 1: Changes in rain and Extreme Degree Day averages in the U.S. Midwest for June, July and August, 1971-2019. Figure 1(a) displays the change in daily mean county rain in the U.S. Midwest and in individual states across time. Figure 1(b) displays the change in daily mean EDD for the U.S. Midwest and individual states across time. Figure 1(c) displays differences in county mean daily rain between 2000-2019 and 1971-1990. Figure 1(d) displays differences in county mean daily EDD between 2000-2019 and 1971-1990. Error bars in figures (a) and (b) represent 95% confidence intervals.

quencies from June to August in each year between 1971 and 2019. Spatially averaged daily rain was 31.6 tenths of a mm. Regressions of spatially averaged daily precipitation as functions of time uncover a positive trend for the 1971-2019 period with an average yearly increase of 0.113 tenths of a mm in daily rain. (Extended Data, columns (1)-(4) of table A.2). This trend suggests an increase of approximately 5.5 tenths of a mm between the start and the end of our sample period. The cumulative effect of trending rain is apparent in the comparison of precipitation measures for various time intervals anchored at the start and end of the 1971-2019 period. Figure 1(a) shows a strongly significant increase in June-August precipitation for the U.S. Midwest and for all of its states across time periods. Results for change in mean tests for average daily rain in earlier and later periods in our sample (1971-1990 vs 2000-2019 and 1971-1985 vs 2005-2019) are in (Extended Data, columns (1)-(4) of table A.3). Figure 1(c) shows the percentage difference in summer precipitation in U.S. Midwest counties, comparing the 1971-1990 period against 2000-2019. Although some counties had a decline in mean precipitation, the rise was largely homogeneous in space and important in magnitude. Alternative tests with year fixed effects rather than a constant yearly trend show that multiple years towards the end of our sample period had significantly higher summer precipitation than those in the earliest part of the sample (Extended Data, columns (1)-(4) of table A.4). In sum, across econometric specifications we find a statistically and agronomically large increase in rain during the growing seasons between 1971 and 2019. Increases in average and extreme rain in the Midwest and other U.S. regions have been reported in earlier work [Kunkel et al., 2003, Arguez et al., 2012, Feng et al., 2016, Mueller et al., 2016, Dav-

enport and Diffenbaugh, 2021, Davenport et al., 2021]. Attribution of rain increase to anthropogenic warming has gained strength in recent years but natural decadal climate variability should not be disregarded [Armal et al., 2018, Lesk and Anderson, 2021]. We interpret the magnitude of our estimates as evidence of changing weather patterns but refrain from claiming a direct causal link to global warming.

Tests for changes in spatially averaged extreme summer temperature measures in the U.S. Midwest were much less conclusive than for rain. We focus our analysis on Extreme Degree Days (EDD), defined for a given day and location as a piecewise linear function that takes the value of zero if local daily temperature is below 30 degrees Celsius and the linear excess over this threshold otherwise. EDD has been widely validated in the literature as a measure of high temperature that is harmful for U.S. Midwest crops [Schlenker and Roberts, 2009]. In contrast with rain, we find that EDD showed no consistent yearly trend when averaged over the U.S. Midwest (Extended Data, columns (5)-(8) of table A.2). Figure 1 (b) and estimates in (Extended Data, columns (5)-(8) of table A.3) show no consistent regional pattern of significant differences in EDD across decades. While the eastern and southern edges of the U.S. Midwest seem to have warmed up slightly on average, this is not the case for its central part that exhibits many instances of cooling (Figure 1 (d)), as in Mueller et al. [2016]. A yearly fixed effect analysis (Extended Data, columns (5)-(8) of table A.4) also shows no clear pattern of an increase in extreme temperatures across decades.

The literature [Mueller et al., 2016, Butler et al., 2018] has found a decrease in extreme heat events in certain parts of the U.S. Midwest by studying centennial

trends, differences across non-consecutive decades and agricultural intensification at the county and weather station level. Perhaps as a consequence of our spatial averaging, and unlike the case of rain, we find no consistent pattern of summer temperature changes across the U.S. Midwest as a whole since 1971.

Weather patterns in the U.S. Midwest during the summer are often the consequence of structured fronts that tend to flow eastwards and last for several days. These are widely followed by farmers and market participants. Thus, we construct weather events defined by patterns of precipitation that last several days. We define a dry spell (wet spell) as a sequence of two or more consecutive days in which the measure of spatially averaged daily rain was below (above) 30 tenths of a mm for every day in the event. Because 30 tenths of a mm was the mean daily precipitation for 1971-1990, dry and wet spells can be interpreted as episodes of precipitation above or below the level expected by market participants based on earlier experience.[2] In addition, days that do not belong in a dry or wet spell are assigned to a normal weather event. In this manner, summers are decomposed as a sequence of three types of weather events that alternate along time. Details of the weather event construction are in (Methods, section *4.2.*). Summary statistics for weather events are in (Extended Data, table A.5).

[2]Nearby thresholds, including 31.6 tenths of a mm that was the average daily rain for 1971-2019, led to a very similar set of events.

2.2. Hot dry spells and heavy rain led to lower yields and increases in new crop prices

An extensive literature has found that crop yields in the U.S. Midwest display an inverted-U response to summer precipitation and a strongly decreasing response to EDD [Tannura et al., 2008, Schlenker and Roberts, 2009, Miao et al., 2016, Lesk et al., 2016, Vogel et al., 2019]. We build on these findings to propose a model for the relationship between weather shocks, changes in expected terminal yields and market returns. We focus on the response of corn and soybean yields to weather shocks that occurred in the U.S. Midwest during June, July and August, which are months after planting and before harvest for these crops. Changes in expected output during these months are largely determined by weather. A model for the nonlinear relationship between local yields, local rain and temperature is presented in (Methods, section *4.4.*). We estimate this model using a panel of yearly county-level data on yields regressed on county-level weather measures recorded monthly for the year in which the yield is observed. Regression specifications are in (Methods, section *4.5.*). This approach takes advantage of yields' rich spatial heterogeneity while being aligned with yields' low time frequency. Estimated models in (Extended Data, table A.6) show strongly significant linear and quadratic rain coefficients for both crops, in line with the notion that very dry or excessively rainy months hurt crops, and a generally negative response to EDD. Figure 2 (a) displays predicted yields as a function of monthly precipitation for various levels of monthly EDD. Point estimates for average rainfall magnitudes that maximized predicted corn and soybeans yields (Methods, section *4.5.*) were 1,714 and 1,729 tenths of mm per

month, respectively, or approximately 56 tenths of a mm per day. These optimal precipitation levels are close to earlier estimates [Tannura et al., 2008, Miao et al., 2016]. In addition, the correlation between spatially averaged monthly rain and EDD in 1971-2019 was -0.29, with dry months frequently having EDD above 20 and no month simultaneously having rain above 1,500 tenths of a mm and EDD above 3. Hence, most harmful months were those either excessively rain yet cool, or simultaneously hot and dry.

Informed by the nonlinear response of yields to weather shocks, we test for the market response to the accumulation of precipitation or temperature away from their optimal levels for crop growth. Unlike yields, which are observed once a year, market prices are available every trading day during the summer. We work with futures contracts that are traded daily at the CME during the growing season and expire in November (for soybean) or December (for corn) of each year in our sample. A futures contract essentially endows its buyer with the right and obligation to acquire a certain crop on expiration date in exchange for the price set by the market at the original trading date. Futures prices for a fixed delivery date fluctuate during the growing season in response to variations in expected supply driven by weather shocks. In our market return estimations we choose to work under the time frequency dictated by the duration of dry spells, wet spells and normal events. There are on average 19.6 events per summer in 1971-2019 (Extended Data, table A.5) hence this frequency allows us to exploit the rich contemporaneous variation in market prices in response to the potentially substantial rain and temperature deviations associated with weather events. We associate with each weather event a precipitation magni-

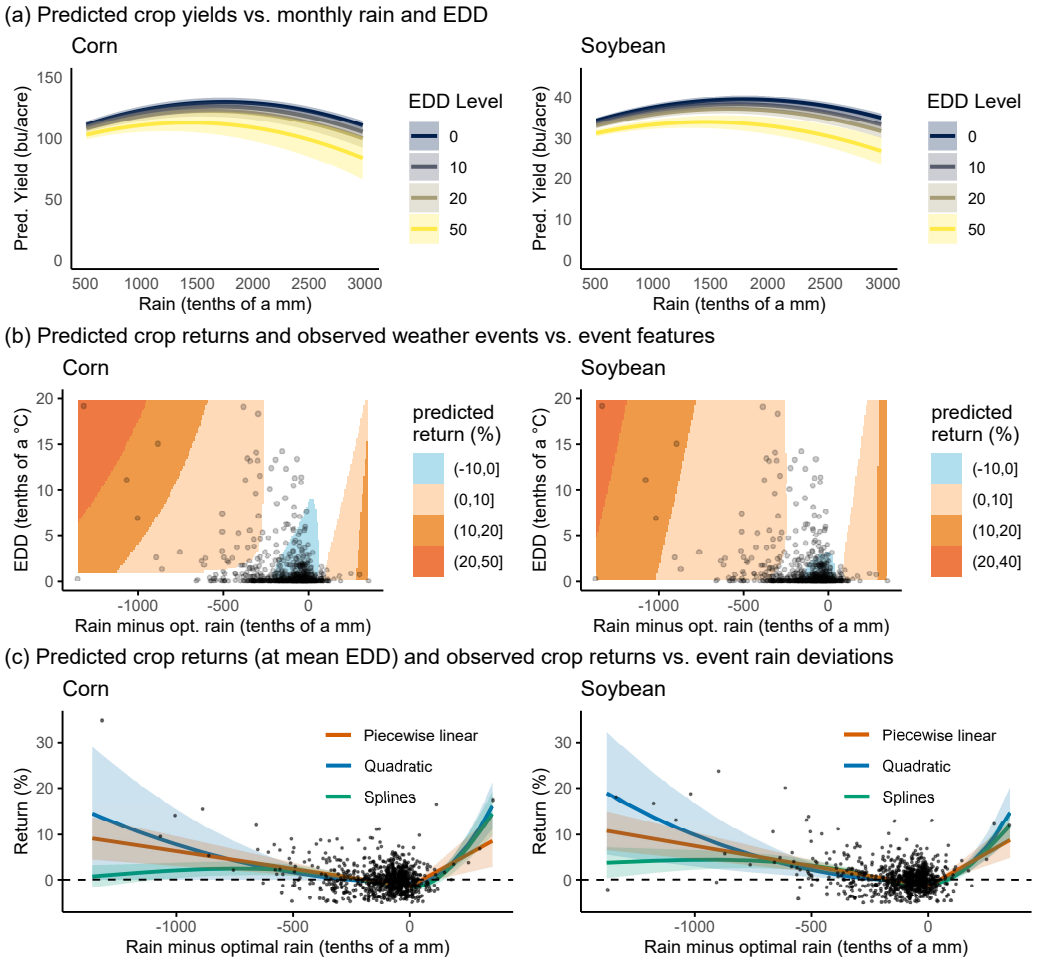


Figure 2: Figure (a) displays predicted corn and soybean yields for monthly precipitation and various levels of monthly EDD, estimated on county-level data. For displaying purposes, all three months in the summer are assumed to have the same monthly rain and EDD. Bands represent 95% confidence intervals for fitted models. Estimates are in (Extended Data, table A.6). Figures (b) displays observed weather event features and predicted market returns as a function of precipitation deviations and EDD over the entire U.S. Midwest. Shown in color are predicted values that are statistically different from zero at the 5% significance level. Figure (c) displays market returns contemporaneous with weather events and alternative fitted models as a function of precipitation deviations over the U.S. Midwest. Bands represent 95% confidence intervals for fitted models. Estimates for figures (b) and (c) are in (Extended Data, table A.7).

tude defined as the amount of rain fallen during the duration of the event minus our yield-based point estimate for optimal monthly precipitation linearly scaled by the length of the event measured in days. The model in (Methods, section *4.4.*) accounts for price changes driven by weather shocks by equation (Methods, (4)). Our base model is piecewise quadratic on precipitation deviations to estimate the impact of insufficient and excessive rain separately. For robustness, we estimate alternative models by regressing crop market returns on piecewise linear and spline functions of contemporaneous precipitation deviations. All specifications include EDD, GDD, interaction terms and economic controls (Methods, section *4.5.*). Estimated coefficients are in (Extended Data, table A.7). Under the baseline piecewise quadratic model, returns for both crops exhibited strongly significant positive response to excessive precipitation events. Rain deficits led to positive returns, strongly in soybeans but not conclusively in corn. Under the piecewise linear model, which also allows for a non-monotone market response to rain, both insufficient and excessive rain contributed to higher crop prices. The interaction term defined as the product of precipitation deviation and EDD was strongly negative in the case of corn for all three specifications. This suggests that episodes that combined rain deficits with high temperatures led to higher corn prices. Figure 2 (b) shows precipitation deviations and EDD for weather events (capped at EDD = 20 for displaying purposes), and predicted market returns estimated from contemporaneous weather events (at mean values for other regressors) using estimates from the quadratic specification in (Extended Data, table A.7). Figure 2 (b) shows that dry spells often coincided with high temperatures while excessive precipitation was associated with cooler weather.

We find that predicted market returns for hot dry spells and strong wet spells were significant and positive. In extreme cases, in excess of a 10% price increase, which implies a large economic impact. In addition, optimal precipitation under mild temperature was associated with negative returns. Predicted returns for all specifications in (Extended Data, table A.7) are computed at mean EDD and presented together with observed market returns in Figure 2 (c). Precipitation deviations contributed towards significantly positive returns. Fitted models in figure 2 (c) provide a conservative estimate for the strength of dry spells impact because, as seen in Figure 2 (b), precipitation deficits had positive correlation with high EDD, which also contributes towards positive returns.

Potential concerns about the results behind figure 2 could include lack of robustness with respect to our event time frequency or to the definition of rain deviation in terms of a predetermined optima. To alleviate these potential concerns we run return regressions of weekly market returns on contemporaneous unnormalized precipitation data and let the estimation identify the amount of rain, if any, that minimizes returns. Results in (Extended Data, table A.8) show that market returns for both crops have negative linear and positive quadratic responses to weekly precipitation. Combined, the terms that involve precipitation imply a nonlinear response that contributes towards positive returns for both low and high weekly precipitation. Point estimates for the amount of weekly rain that minimizes returns are at 280 and 266 tenths of a mm for corn and soybean, respectively. This is approximately 30% lower than the optimal precipitation inferred from yield regressions in (Extended Data, table A.6) on monthly data and linearly scaled to weekly frequency. Beyond estimation noise,

potential explanations for this difference include a more nuanced relationship between yields and rain than in (Methods, (2)), monthly vs weekly estimation frequencies, and forms of risk aversion among market participants that would bring prices away from fundamentals. Unreported results on daily frequency were less significant than those presented in this paper. We attribute this to a signal to noise ratio in daily data that is lower than that implicit in longer precipitation events which allows for an agronomically significant accumulation of rain and heat. We also considered regression specifications using the contribution of the U.S. Midwest to global output, rather than U.S. output, as weighting factor for weather shocks. This is to reflect that CME prices aggregate to some extent supply and demand beyond the U.S. Estimated coefficients imply quantitatively similar weather price impact after adjustment for the change in weighting. This simply reflects that market shares are very slowly moving variables across decades and unrelated to short-term weather fluctuations. Finally, we conduct a placebo test regressing market price returns for wheat, which is a winter crop, during the growing season for corn and soybeans. Our estimates (Extended Data, table A.9) find no effect for summer weather shocks on wheat. In sum, given the simplicity of our model for yields and returns, and the noise around our estimates, we interpret our results as generally supportive for the notion that agricultural commodity markets were pricing the nonlinear impact of weather variables in manner that was compatible with production fundamentals.

2.3. Crop prices increasingly responded to excessive precipitation

In the previous section we found that, over the full 1971-2019 sample, hot dry spells and excessive rain events were conducive to higher crop prices. Has the significance of these two kinds of events changed as precipitation gained strength in the U.S. Midwest between 1971 and 2019? We explore this question by estimating the model in (Methods, *4.4.*) on the two earliest and two latest decades in our sample. These are time intervals sufficiently long for statistical estimation, yet far enough from each other in time to differ in their weather patterns (figure 1). Yield estimates are in (Extended Data, table A.10). Figure 3 (a) displays fitted models for corn and soybean yields as a function of monthly precipitation for various levels of EDD. Maximum crop yields in 2000-2019 were substantially higher than those in 1971-1990, driven partially by agronomic practices and technology [Rizzo et al., 2022].

Figure 3 (b) displays fitted piecewise quadratic models for corn and soybean market returns in 1971-1990, as a function of precipitation deviations and EDD, while holding other variables at their mean levels. Estimates are in (Extended Data, table A.11). In this exercise we use deviations from optimal rain estimates based on 1971-2019 (Extended Data, table A.6). In 1971-1990, hot dry spells made a statistically strong and positive contribution to corn and soybean returns mediated by the interaction term in the estimated model. Figure 3 (b) also shows that high temperatures under optimal precipitation made a negative contribution to corn returns and had no significant effect on soybean returns. In 2000-2019, episodes of excessive precipitation were stronger than in 1971-1990. Mean and maximum wet spells increased

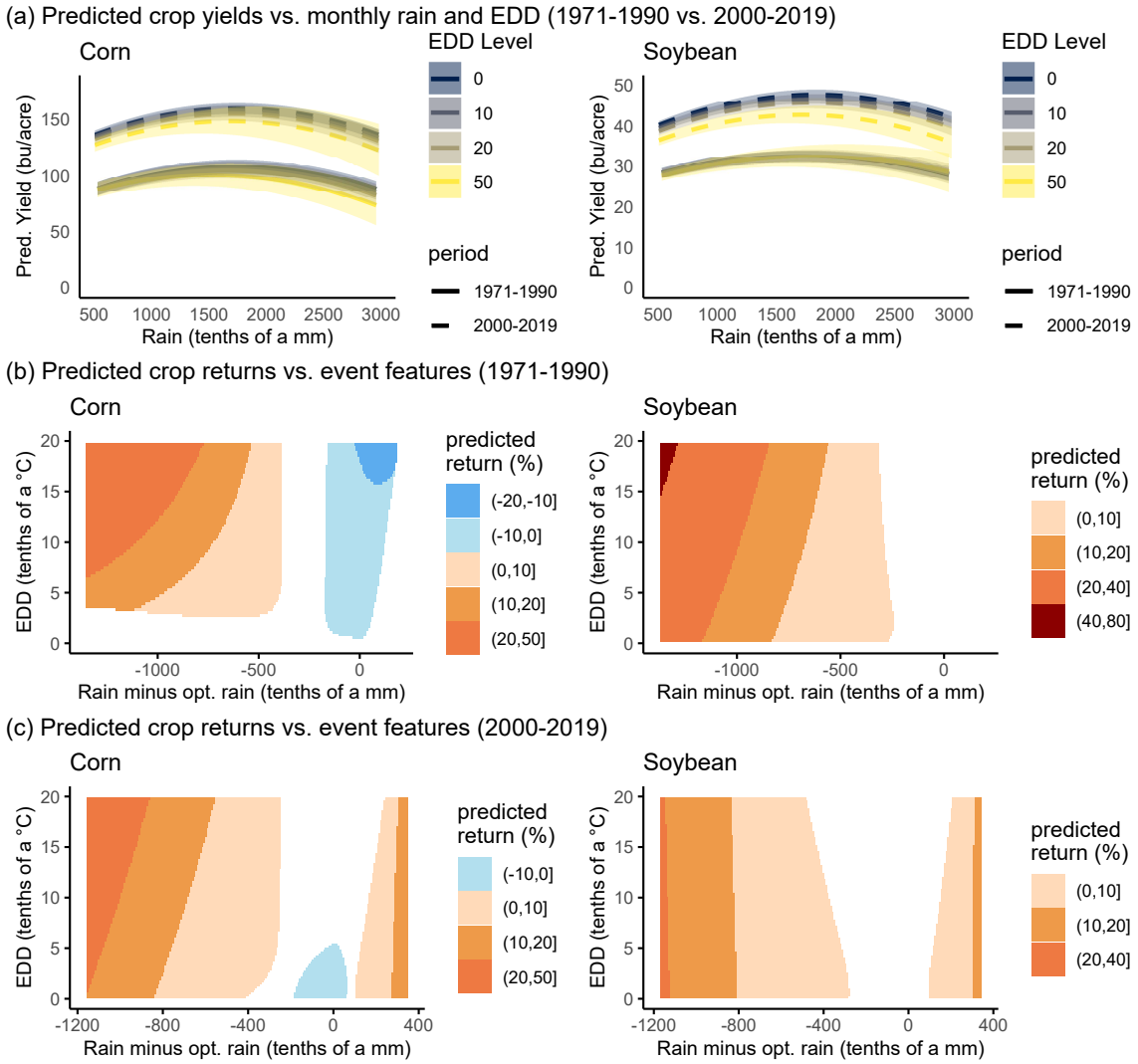


Figure 3: Figure (a) displays predicted corn and soybean county yields for monthly precipitation and various levels of EDD, estimated on county-level data. For displaying purposes, all three months in the summer are assumed to have the same monthly rain and EDD. Bands represent 95% confidence intervals for fitted models. Estimates are in (Extended Data, table A.10). Figures (b) and (c) display predicted market returns as a function of precipitation deviations and EDD for the entire U.S. Midwest. Shown in color are predicted values that are statistically different from zero at the 5% significance level. Estimates are in (Extended Data, table A.11).

from 171 and 621 in earlier decades to 196 and 800 tenths of a mm in later decades (Extended Data, table A.5). Figure 3 (c) shows that, as larger precipitation events materialized in 2000-2019, excessive rain became statistically significant in contributing to positive returns in both crops. Interaction terms for precipitation and EDD seemed to weaken in magnitude and remained significant only for corn in the last two decades of our sample. As robustness, we also consider rain deviations defined in terms of optimal precipitation estimated separately for each crop and period. Point estimates for optimal mean daily precipitation were close to 54 and 48 tenths of a mm for corn and soybeans, respectively, during 1971-1990, and at 58 and 59 tenths of a mm during 2000-2019. Results in (Extended Data, figures B.2 (a,b) and table A.12) largely agree with figure 3. Hence, we find that shifting weather patterns in the U.S. Midwest were mirrored by market responses consistent with production fundamentals.

3. Discussion

The main contribution of this paper is a characterization of the effects of extreme weather and changing weather patterns in the U.S. Midwest, a major producing region, on new crop corn and soybean prices. We began by documenting a positive trend in summer precipitation in the U.S. Midwest between 1971 and 2019. Spatially averaged summer precipitation increased by approximately 15% between 1971 and 2019. Spatially averaged extreme temperatures did not show a changing pattern during this period. Next, we found that dry spells contributed to higher prices and that this effect was amplified by extreme heat in the form of EDD. Hot dry spells

led to predicted CME price increments potentially in excess of 10%. This is highly significant in economic terms. In more recent decades, as precipitation became more intense, events associated with excessive rain contributed more strongly towards positive market returns. This effect was not visible in the first twenty years in our sample. The nonlinear market response to precipitation and EDD was generally consistent in its shape with the estimated impact of rain and temperature on yields. In this paper we estimate the response of crop prices to contemporaneous weather events. We do not explore the effect of extreme weather events on long term or multi-year prices. But, as short term weather shocks have a real impact on yields and market participants are rational and forward looking, it is sensible to interpret these price movements as non-transient in the context of the current season. Advances in agronomic practices, including adaptation in response to climate change [Mase et al., 2017, Hatfield et al., 2018, Liu and Basso, 2020, Sloat et al., 2020, Rising and Devineni, 2020], are likely to mitigate the impact of weather on yields and might have modulated the impact of weather on markets. Disentangling the precise time-varying contribution of climate adaptation from the high-frequency link between weather and crop prices is challenged by the lack of spatial variability in prices. Increase in irrigation, that as of 2024 is still used in a very minor proportion of corn and soybean farms in the U.S. Midwest, could weaken the link between scarce rain and returns but could potentially strengthen, through evapotranspiration, the market impact of excessive precipitation [Mueller et al., 2016].

Our findings complement earlier work on the effect of shifting weather patterns on agriculture in the U.S. Midwest [Schlenker and Roberts, 2009, Mueller et al., 2016,

Tollenaar et al., 2017, Butler et al., 2018, Rizzo et al., 2022]. An explicit distinction has been made [Lesk et al., 2020] between the positive impact of higher precipitation on U.S. corn and soybean yields, and the negative yield impact of the most extreme hourly rain episodes. We find that for rain to contribute to higher prices, it must be not just higher than the historical average (31.6 tenths of a mm per day) but also surpass a larger agronomical optimal. This suggests that market participants are aware of the differential impact of various rain magnitudes. The market impact of dry heat in corn is consistent with the damage provoked by extreme dry heat on yields [Ting et al., 2023]. Our paper is an early contribution to a research agenda on valuation and risk management in crop markets under climate risk. Potential avenues for future work include quantifying the impact of compound extremes in market prices [Haqiqi et al., 2021, Ting et al., 2023], exploring the interplay between weather shocks, planting decisions during spring and market returns; and exploring the empirical performance of more complex models that condition the impact of an extreme weather event on moisture or accumulated precipitation since the start of the summer.

Our findings suggest that the negative effects of extreme weather on agricultural output and economic activity would also operate through sharp price increases with potential redistributive effects. Local farmers affected by a negative output shock could be partially compensated by higher prices [Sajid et al., 2023]. Given the integrated nature of corn and soybean markets, producers in Brazil, Argentina and elsewhere could benefit from higher prices [Headey and Hirvonen, 2023]. And consumers around the world would face higher costs, increased volatility and potential

food insecurity [Ahmed et al., 2009, Nelson et al., 2014, Bellemare, 2015, Headey and Martin, 2016, Haile et al., 2017, Davis et al., 2021, Hasegawa et al., 2021, De Winne and Peersman, 2021]. Corn price spikes would also interact with the energy sector through the ethanol mandate [Diffenbaugh et al., 2012]. Coupling our estimated crop price responses with long-term forecasts from large scale climatological models may contribute to better long-term economic forecasts and food price volatility estimates.

4. Methods

4.1. Weather data

We obtained daily precipitation and temperature data from NOAA (National Oceanic and Atmospheric Association)'s GHCN (Global Historical Climate Network) dataset. We focus on data for June, July and August in the U.S. Midwest from 1971 to 2019. Some weather stations have missing data on certain dates, so we kept for our regressions those that cover (i.e. have non-missing data) at least 50% of the period. This left us with 1,311 weather stations for precipitation and 960 stations for temperature, roughly evenly distributed across the twelve states of the Midwest (figure B.1, Extended Data). Table A.1 (Extended Data) displays summary statistics for our raw weather data. Rain and temperature are reported in daily and monthly frequencies, and averaged over the U.S. Midwest. In line with the literature, we report summary statistics for Growing Degree Days (GDD) and Extreme Degree Days (EDD), which measure the exposure that crops have experienced to healthy growing conditions and to excessively hot weather, respectively.

4.2. Weather events

We decompose each summer in a temporal sequence of weather events in which dry, normal and wet spells alternate with each other during summers from 1971 to 2019. We proceed as follows. Let R_t be the spatial average of rain fallen over the U.S. Midwest on day t, where all seven days of the week are treated equally. Let F_t represent rain information learnt by market participants on trading day t. We adopt $F_t = R_t$ except for Mondays in which $F_{monday} = R_{saturday} + R_{sunday} + R_{monday}$ to incorporate information on the most recent weekend. A wet spell is defined as two or more consecutive trading days where F_t in each trading day is above a certain threshold. For Tuesdays to Fridays, we set the threshold at 30 tenths of a mm, which is close to the mean daily rain for the 1971-1990 period. For Mondays, the threshold is 90 tenths of a mm to account for the fact traders incorporate on this day information revealed during the weekend. A dry spell is two or more consecutive days with F_t lower than the aforementioned thresholds. Days not in a wet or a dry spell belong to a normal event. Defined in this manner, wet spells can be interpreted as multi-day events with higher than usual rain.

4.3. Additional data sources

Data on corn and soybean futures contracts prices were gathered from Reuters Datastream. From Federal Reserve Economic Data St. Louis we gathered daily data on spot crude oil price (WTI). We use the "Nominal Broad Dollar Index – Goods Only" from the Federal Reserve Bank for a measure of the exchange rate/strength of the U.S. dollar. Our choice of controls is standard in the literature. The oil price is

included as a control as it relates to global commodity demand and crop production costs. To account for demand fluctuations, we also considered the Baltic dry index on a daily basis since 1985. Corn and soybean yields per state, inventories and planted area on yearly frequency were gathered from the USDA.

4.4. A model for weather and crop returns

An extensive literature relates weather to crop yields. Schlenker and Roberts [2009] relied on U.S. data between 1950 and 2005 to find that corn and soybean yields had an inverse U-shaped response to rain during the growing season from May to August. Rain is beneficial to crops up to a certain threshold. Beyond that, crops suffer. Crop yields were slightly increasing as a function of temperature up to the vicinity of 30 degrees Celsius, and sharply decreasing after exposure to temperatures beyond that threshold. Using data for the United States from 1977 to 2007, Miao et al. [2016] found that corn and soybean yields had an inverse U-shaped response to monthly rain during June, July and August. They also found corn and soybean yields positively related to Growing Degree Days and negatively related to Extreme Degree Days[3]. In earlier work, Tannura et al. [2008] used data between 1960 and 2006 for Indiana, Illinois and Iowa, to find an inverted-U relationship between corn and soybean yields in the U.S. Midwest and rain in each of the months of June, July and August. These works find that corn and soybean yields are generally increasing for up to the vicinity of 6 inches (1,524 tenths of mm) of monthly summer rain and tend to decrease for heavier precipitation. Schlenker and Roberts [2009] report that the nonlinear relationship between yield and temperature between 1950 and 1977

[3]Defined as Overheat Degree Days in Miao et al. [2016]

was the same as the one between 1978 and 2005.

We explore the effect of weather shocks on the dynamics of crop prices. Farmers in twelve states in the U.S. Midwest grow corn and soybeans and sell their output in a competitive market. We focus on corn and soybean price changes during a single growing season, after seeds have been planted at $t = 0$. This allows us to assume that output variations at harvesting time T at the end of the summer are due to yield variability caused by weather shocks in June, July and August, and not due to planting decisions. Regional output is harvested at T and added to typically small existing stocks, for final supply Q_{year}. Expected supply, conditional on information available to participants at the Chicago Mercantile Exchange during the growing summer at time $t \leq T$ is

$$E_t[Q_{year}]. \tag{1}$$

Uncertainty about supply at harvesting time is a function of the yield per unit of land, which depends on technology chosen prior to the growing season and on weather. In the absence of significant irrigation, as it is the case for the vast majority of corn and soybeans in the U.S. Midwest, water intake is provided exclusively by rain. We split the summer in non-overlapping periods $j = 1, ..., N$, to model the link between weather and terminal yields on time periods that allow for the accumulation of a significant amount of rain or heat. Let R_j, GDD_j and EDD_j be the spatial averages of rain, Growing Degree Days and Extreme Degree Days that occurred during period j over the U.S. Midwest. Let $Y_{year,T}$ be the terminal yield that will be observed at T in $year$. Based on the nonlinear relationship between weather and yields identified

in the literature [Schlenker and Roberts, 2009], we postulate that

$$Y_{year,T} = Y_{year,0}(1 + \sum_{j=1}^{N}[\alpha_0 + \alpha_1(R_j - R^*)^2 + \alpha_2 GDD_j + \alpha_3 EDD_j]). \quad (2)$$

where $\alpha_1 < 0, \alpha_2 > 0, \alpha_3 < 0$, and $Y_{year,0}$ is the predictable component of trending yields across years due to technological innovation. In this expression, R^* is the agronomically optimal amount of rain. Insufficient or excessive precipitation hurts crops. In the case of a monthly partition for the summer, earlier estimates suggest R^* in the vicinity of 1,500 - 1,600 tenths of a mm [Tannura et al., 2008].

Market expectations of terminal output are updated during the summer. We assume that short-term weather shows no predictability in time beyond very short-term forecasts available at the start of period j. Therefore, the change in expected terminal output that occurs during period j depends on weather measures revealed contemporaneously. Let E_j be the conditional expectation based on information available at the start of period j. Taking conditional expectations in (2) we write

$$E_{j+1}[Y_{year,T}] - E_j[Y_{year,T}] = Y_{year,0}(\alpha_1(R_j - R^*)^2 + \alpha_2 GDD_j + \alpha_3 EDD_j - EW), \quad (3)$$

where EW is the unconditional expectation of weather shocks (precipitation and temperature) for period j. Weather-related contributions in (2) associated to periods other than j are either known if they already occurred, or have the same conditional expected value as seen from periods j and $j+1$. Hence, they all cancel away and do not contribute to (3). The change in expected output in period j is driven exclusively by weather shocks at j. Let P_j^T be the price observable at $j \leq T$ associated with a Chicago Mercantile Exchange future contract expiring at T. Let A_{year} be the

planted area in the U.S. Midwest so that terminal supply is $Q_{year} = A_{year}Y_{year,T}$. Under a standard model for supply and demand for T, with constant elasticities and multiplier $\beta > 0$ [Varian, 2014], the percentage price change between the start of period j and the start of period $j+1$ due to an exogenous supply shock is

$$\frac{P^T_{j+1} - P^T_j}{P^T_j} \approx -\beta W^{Midwest}_{year}(\alpha_1(R_j - R^*)^2 + \alpha_2 GDD_j + \alpha_3 EDD_j - EW), \tag{4}$$

where

$$W^{Midwest}_{year} = \frac{A_{year}Y_{year,0}}{US\,Output_0 + Inventories_0} \tag{5}$$

is a measure of the importance of U.S. Midwest production in the U.S or global market for corn or soybeans (before being multiplied by local yield variations). Crop prices are also influenced by global demand fluctuations that we assume uncorrelated to local weather. These and other financial variables are taken into consideration in the empirical estimation of the model through appropriate controls.

4.5. Regression specifications

Our regressions for yields on weather data are motivated by (2). To uncover the response of yields to weather shocks, including the precipitation amount that maximizes yields, we regress

$$\begin{aligned} Y_{c,y} = &\sum_{m=June}^{August} \beta_{1,m} R_{c,y,m} + \sum_{m=June}^{August} \beta_{2,m} R^2_{c,y,m} + \sum_{m=June}^{August} \beta_{3,m} GDD_{c,y,m} + \\ &+ \sum_{m=June}^{August} \beta_{4,m} EDD_{c,y,m} + \sum_{m=June}^{August} \beta_{5,m} EDD_{c,y,m} R_{c,y,m} + \mu_c + \lambda_y + \epsilon_{c,y}. \end{aligned} \tag{6}$$

The subscripts in (6) refer to individual counties (c), year (y) and month (m = June, July and August). Y is the annual yield (measured in bushels per acre), and R, GDD and EDD are, respectively, rain, Extreme Degree Days and Growing Degree Days accumulated over a month during the summer. County-fixed effect μ_c controls for average county yield, and year-fixed effect λ_y for time-varying regional shocks common to all counties. These parameters seek to control for technological change, among other non weather-related factors. The amount of precipitation that maximizes the contribution of pure rain terms to yields is $\frac{-\beta_{1,m}}{2\beta_{2,m}}$. In the presence of a significant interaction term, the amount of rain that maximizes yields can be approximated by $\frac{-\beta_{1,m}-\beta_{5,m}\overline{EDD}}{2\beta_{2,m}}$ where $\overline{EDD}$ is the mean value of EDD. Based on 1971-2019 monthly data and averaged over the summer, estimates for optimal rain for both definitions and crops lie between 52 and 57 tenths of a mm per day. In addition, we show in (Extended Data, tables A.8, A.11 and A.12) that our findings for the market response to extreme precipitation are robust to small variations in R^*. Our regressions for crop returns on weather data are grounded on (4) and their structure is

$$\begin{aligned}\frac{P_{j+1}^T - P_j^T}{P_j^T} &= \beta_0 + \beta_1 W_j (R_j - R_j^*)^2 \mathbb{1}\left[(R_j - R_j^*) > 0\right] \\ &+ \beta_2 W_j (R_j - R_j^*)^2 \mathbb{1}\left[(R_j - R_j^*) < 0\right] \\ &+ \beta_3 W_j EDD_j + \beta_4 W_j GDD_j + \beta_5 W_j (R_j - R_j^*) EDD_j \\ &+ Controls_j + \epsilon_j, \quad j = 1, ..., N_{periods},\end{aligned} \tag{7}$$

where $\frac{P_{j+1}^T - P_j^T}{P_j^T}$ is the percentage price change, or return, of a crop future contract

during time period j. The optimal amount of rain R_j^* is simply the R^* estimated from yields and monthly rain, linearly scaled by the length of period j in days. Hence, $R_j - R_j^*$ can be interpreted as the deviation from optimal precipitation contemporaneous to the crop market return. The weight W captures the share of the U.S. Midwest in the market for that crop. In our empirical work we construct a measure for W_j using physical production forecasts and inventories measures available on May of each year and leave W_j constant during each summer. Bruno et al. [2017] consider low frequency inventory measures constructed from USDA published statistics (therefore already in physical units) and a higher frequency inventory proxy given by the slope of the term structure that correlates strongly with inventories but has no physical units. Because the determination of P_j^T depends on the combined effect of expected global output at T and available inventories in the denominator of (5), we choose to work with statistics published in May of each year on existing inventories and expected output. Standard controls to explain price changes, when available in the frequency of our weather variables, are the contemporaneous returns on the WTI spot crude oil price, the Nominal Major Currencies Dollar Index (Goods Only) from the U.S. Federal Reserve, the Baltic Dry Index that captures global commodity demand. By working with returns and local shocks, all variables included in (7) are stationary and all regressors are plausibly exogenous.

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6. Author contributions

NM and MC conceptualized and designed the study and wrote the original draft. MC, NM and EM collected and analyzed data. All authors edited and reviewed the paper.

7. Data Availability

Code and data to perform all the analyses and produce the tables and figures in this paper are available at: https://codeocean.com/capsule/7312575/tree

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8. Extended Data

Table A.1: Summary statistics for weather variables and market returns.

Variable	Min	Mean	Median	Max	SD	N
Daily Rain (tenths mm)	0.0	31.6	25.5	191.6	24.6	4508
Daily GDD (tenths deg Celsius)	34.5	141.5	143.3	205.5	26.7	4508
Daily EDD (tenths deg Celsius)	0.0	0.2	0.0	7.7	0.6	4508
Monthly Rain (tenths mm)	376.3	969.2	951.9	1838.5	263.6	147
Monthly GDD (tenths deg Celsius)	2997	4338	4346	5647	511.4	147
Monthly EDD (tenths deg Celsius)	0.0	6.2	2.2	95.9	11.5	147
Event corn return (%)	-14.56	-0.20	-0.32	35.48	3.72	961
Event soybean return (%)	-16.42	-0.01	-0.10	23.69	3.57	961
Event wheat return (%)	-17.34	0.04	-0.09	26.48	3.18	961

Notes: Daily rain is spatially averaged across the U.S. Midwest. GDD at the weather station level is constructed as a step function: it is zero if the local daily mean temperature is below 80 tenths of degree Celsius, it takes the value of mean temperature minus 80 if the mean temperature for the day is between 80 and 300 tenths of degree Celsius and it takes the value of 220 if mean temperature is above 300 tenths of degree Celsius. Daily and monthly GDD cannot be negative and are bounded by 220 and 6,820, respectively. Daily EDD is a step function that takes the value of zero if mean temperature is below 300 tenths of degree Celsius and takes the value of mean temperature minus 300 if mean temperature for that day is above 300 tenths of degree Celsius. Daily and monthly EDD cannot be negative and are not bounded from above. Monthly rain, Monthly GDD and Monthly EDD are, respectively, the sum of daily rain, daily GDD and daily EDD within a month. Corn, soybean and wheat returns are computed over the duration of weather events.

Table A.2: Regressions for spatially averaged daily rain and Extreme Degree Days (EDD) on daily summer and yearly trends in 1971-2019.

	Rain (tenths of a mm)				EDD (tenths of deg Celsius)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily trend		-0.094^{***}	-0.284^{***}	-0.381^{*}		0.001^{***}	0.016^{***}	0.019^{***}
		(0.022)	(0.083)	(0.219)		(0.0005)	(0.003)	(0.007)
Daily trend^2			0.002^{**}	0.005			-0.0002^{***}	-0.0002
			(0.001)	(0.005)				
Daily trend^3				-0.00002				0.00000
				(0.00004)				(0.00000)
Yearly trend	0.113^{***}	0.113^{***}	0.113^{***}	0.113^{***}	-0.0002	-0.0002	-0.0002	-0.0002
	(0.042)	(0.041)	(0.040)	(0.040)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	28.770^{***}	33.147^{***}	36.115^{***}	36.890^{***}	0.205^{***}	0.139^{**}	-0.087	-0.110^{**}
	(1.157)	(1.441)	(1.908)	(2.451)	(0.054)	(0.061)	(0.056)	(0.056)
Observations	4,508	4,508	4,508	4,508	4,508	4,508	4,508	4,508
Adjusted R^2	0.004	0.014	0.017	0.017	-0.0002	0.003	0.026	0.026

Notes: The daily summer trend is a sequential variable ranging from 1 to 92, representing each day of the summer season from June 1st to August 31st. The yearly trend is a sequential variable ranging from 1 to 49, representing each year of the sample. Heteroskedasticity and autocorrelation consistent (HAC) standard errors reported in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.3: County-level mean differences in daily rain and EDD, averaged by state and region across time periods.

	Rain (tenths of a mm)				EDD (tenths of a deg Celsius)			
	(2000-2019 vs 1971-1990)		(2005-2019 vs 1971-1985)		(2000-2019 vs 1971-1990)		(2005-2019 vs 1971-1985)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Midwest		2.876***		3.860***		−0.019***		0.009
		(0.102)		(0.128)		(0.007)		(0.008)
Illinois	3.080***		3.001***		-0.019		0.045***	
	(0.364)		(0.432)		(0.013)		(0.015)	
Indiana	3.054***		2.885***		0.012		0.032***	
	(0.340)		(0.385)		(0.007)		(0.009)	
Iowa	3.671***		6.183***		-0.081***		-0.031***	
	(0.281)		(0.395)		(0.010)		(0.010)	
Kansas	3.556***		5.527***		0.062		-0.049	
	(0.295)		(0.338)		(0.043)		(0.049)	
Michigan	1.023***		1.848***		0.005*		0.009***	
	(0.322)		(0.385)		(0.003)		(0.003)	
Minnesota	2.069***		2.239***		-0.030***		-0.007**	
	(0.446)		(0.512)		(0.006)		(0.004)	
Missouri	4.808***		5.148***		-0.051*		-0.007	
	(0.337)		(0.414)		(0.027)		(0.033)	
Nebraska	2.448***		4.931***		-0.066***		-0.076***	
	(0.222)		(0.266)		(0.023)		(0.027)	
North Dakota	3.853***		3.973***		-0.014**		-0.004	
	(0.333)		(0.400)		(0.006)		(0.004)	
Ohio	1.171***		1.663***		0.005*		0.015***	
	(0.288)		(0.402)		(0.003)		(0.004)	
South Dakota	3.240***		4.220***		-0.036**		0.015	
	(0.306)		(0.338)		(0.017)		(0.017)	
Wisconsin	1.820***		2.120***		-0.005**		0.015***	
	(0.341)		(0.448)		(0.003)		(0.003)	
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,935,558	2,939,238	2,199,315	2,202,075	2,548,969	2,552,649	1,914,139	1,916,899
R^2	0.0003	0.0003	0.001	0.0005	0.0001	0.00002	0.0001	0.00000

Notes: standard errors in parenthesis were clustered at the county level, *p< 0.1; **p< 0.05; ***p< 0.01.

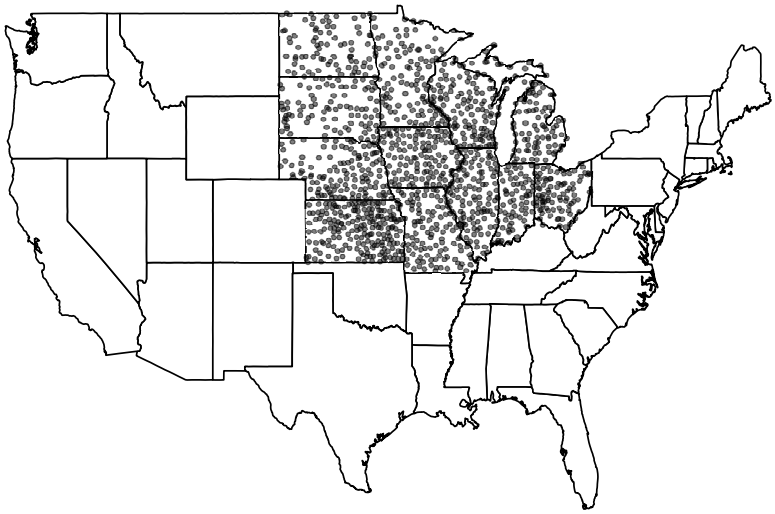


Figure B.1: Spatial distribution of 1311 weather stations in the Midwest.

Table A.4: Regressions for spatially averaged daily rain and Extreme Degree Days (EDD) on daily summer trend and yearly fixed effects (1971-2019).

	Rain (tenths of a mm)				EDD (tenths of deg Celsius)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily trend		−0.094***	−0.284***	−0.381*		0.001***	0.016***	0.019***
Daily trend^2			0.002***	0.005			−0.0002***	−0.0002*
Daily trend^2				−0.00002				0.00000
1972	5.509	5.509	5.509	5.509	−0.055	−0.055	−0.055	−0.055
1973	2.952	2.952	2.952	2.952	0.007	0.007	0.007	0.007
1974	1.493	1.493	1.493	1.493	0.157	0.157	0.157	0.157
1975	6.041	6.041	6.041	6.041	−0.014	−0.014	−0.014	−0.014
1976	−4.835	−4.835	−4.835	−4.835	0.041	0.041	0.041	0.041
1977	9.194*	9.194*	9.194**	9.194**	0.099	0.099	0.099	0.099
1978	5.285	5.285	5.285	5.285	0.158**	0.158**	0.158***	0.158***
1979	9.217**	9.217**	9.217*	9.217*	−0.047	−0.047	−0.047	−0.047
1980	6.497	6.497	6.497	6.497	1.268**	1.268**	1.268***	1.268**
1981	11.730**	11.730***	11.730***	11.730***	0.040	0.040	0.040	0.040
1982	6.032	6.032*	6.032	6.032	−0.010	−0.010	−0.010	−0.010
1983	−1.266	−1.266	−1.266	−1.266	0.506**	0.506**	0.506**	0.506**
1984	−0.346	−0.346	−0.346	−0.346	0.041	0.041	0.041	0.041
1985	5.100	5.100	5.100	5.100	−0.005	−0.005	−0.005	−0.005
1986	7.265	7.265	7.265	7.265	0.042	0.042	0.042	0.042
1987	7.292*	7.292*	7.292*	7.292*	0.102	0.102	0.102	0.102
1988	−4.524	−4.524	−4.524	−4.524	0.580***	0.580***	0.580***	0.580***
1989	4.148	4.148	4.148	4.148	−0.006	−0.006	−0.006	−0.006
1990	9.783**	9.783**	9.783**	9.783**	0.170**	0.170*	0.170**	0.170**
1991	−2.115	−2.115	−2.115	−2.115	0.163*	0.163*	0.163**	0.163**
1992	9.682	9.682*	9.682	9.682	−0.068*	−0.068	−0.068	−0.068
1993	23.466***	23.466***	23.466***	23.466***	−0.032	−0.032	−0.032	−0.032
1994	6.617*	6.617*	6.617	6.617	−0.055	−0.055	−0.055	−0.055
1995	4.821	4.821	4.821	4.821	0.126	0.126	0.126	0.126
1996	5.226	5.226	5.226	5.226	−0.021	−0.021	−0.021	−0.021
1997	5.289	5.289	5.289	5.289	−0.019	−0.019	−0.019	−0.019
1998	10.760**	10.760**	10.760**	10.760**	0.063	0.063	0.063	0.063
1999	5.761	5.761	5.761	5.761	0.134	0.134	0.134	0.134
2000	7.391	7.391	7.391	7.391	0.182	0.182	0.182	0.182
2001	4.462	4.462	4.462	4.462	0.218	0.218*	0.218**	0.218**
2002	2.681	2.681	2.681	2.681	0.128	0.128	0.128	0.128
2003	2.322	2.322	2.322	2.322	0.185*	0.185*	0.185*	0.185*
2004	7.088	7.088	7.088	7.088	−0.059	−0.059	−0.059	−0.059
2005	6.013	6.013	6.013	6.013	0.091	0.091	0.091	0.091
2006	3.105	3.105	3.105	3.105	0.395*	0.395**	0.395**	0.395***
2007	6.804	6.804	6.804	6.804	0.079	0.079	0.079	0.079
2008	8.992	8.992	8.992	8.992	−0.028	−0.028	−0.028	−0.028
2009	8.697**	8.697**	8.697**	8.697**	−0.041	−0.041	−0.041	−0.041
2010	16.286**	16.286***	16.286***	16.286***	0.112	0.112	0.112	0.112
2011	6.860	6.860	6.860	6.860	0.676**	0.676**	0.676**	0.676***
2012	−5.968	−5.968	−5.968	−5.968	0.835**	0.835**	0.835**	0.835**
2013	3.117	3.117	3.117	3.117	0.003	0.003	0.003	0.003
2014	13.360*	13.360**	13.360**	13.360**	−0.020	−0.020	−0.020	−0.020
2015	13.876***	13.876***	13.876***	13.876***	−0.033	−0.033	−0.033	−0.033
2016	11.547**	11.547**	11.547**	11.547**	0.026	0.026	0.026	0.026
2017	4.975	4.975	4.975	4.975	0.041	0.041	0.041	0.041
2018	12.109**	12.109**	12.109**	12.109**	−0.002	−0.002	−0.002	−0.002
2019	10.690**	10.690**	10.690**	10.690**	−0.001	−0.001	−0.001	−0.001
Constant	25.472***	29.848***	32.817***	33.592***	0.075**	0.009	−0.217***	−0.240***
Obs,	4,508	4,508	4,508	4,508	4,508	4,508	4,508	4,508
Adj. R^2	0.047	0.050	0.050	0.017	0.145	0.149	0.172	0.172

Notes: The daily summer trend is a sequential variable ranging from 1 to 92, representing each day of the summer season from June 1st to August 31st. The constant coefficient represent the average of the dependent variable on 1971 for (1) and (5), and on June 1st, 1971 for (2), (3), (4), (6), (7) and (8). Heteroskedasticity and autocorrelation consistent (HAC) standard errors were used but are not reported due to space constraints, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.5: Summary statistics for weather variables by summer event type, across time periods.

Event	Variable	Period	Min	Mean	Median	Max	SD	N
Wet spell	Length (in days)	1971-2019	2.00	4.92	4.00	32.00	3.64	351
	Length (in days)	1971-1990	2.00	4.49	4.00	14.00	2.75	140
	Length (in days)	2000-2019	2.00	5.06	4.00	19.00	3.26	151
Dry spell	Length (in days)	1971-2019	2.00	5.84	5.00	33.00	4.24	368
	Length (in days)	1971-1990	2.00	6.16	5.00	8.00	4.53	157
	Length (in days)	2000-2019	2.00	5.50	4.00	26.00	4.27	151
Normal event	Length (in days)	1971-2019	1.00	2.29	2.00	8.00	1.48	242
	Length (in days)	1971-1990	1.00	2.12	1.50	6.00	1.30	100
	Length (in days)	2000-2019	1.00	2.21	1.00	7.00	1.47	96
Wet spell	Rain (tenths mm)	1971-2019	33.99	190.36	146.70	588.29	159.28	351
	Rain (tenths of a mm)	1971-1990	50.28	171.28	133.12	620.67	110.70	140
	Rain (tenths of a mm)	2000-2019	33.99	195.77	149.40	800.32	148.69	151
Dry spell	Rain (tenths of a mm)	1971-2019	4.34	60.87	48.76	366.37	41.67	368
	Rain (tenths mm)	1971-1990	5.65	62.10	50.35	366.37	43.02	157
	Rain (tenths mm)	2000-2019	4.34	57.74	45.17	251.02	41.44	151
Normal event	Rain (tenths mm)	1971-2019	0.54	44.76	37.34	230.42	32.17	242
	Rain (tenths mm)	1971-1990	1.69	41.37	36.74	152.88	26.46	100
	Rain (tenths mm)	2000-2019	0.54	45.23	38.34	153.49	31.75	96
Wet spell	GDD (tenths deg Celsius)	1971-2019	139.9	694.1	569.5	4497.9	511.5	351
	GDD (tenths deg Celsius)	1971-1990	139.9	629.5	542.0	2232.3	410.3	140
	GDD (tenths deg Celsius)	2000-2019	159.9	722.6	592.3	2743.8	464.74	151
Dry spell	GDD (tenths deg Celsius)	1971-2019	121.1	829.7	655.7	4554.4	652.6	368
	GDD (tenths deg Celsius)	1971-1990	121.1	881.0	682.7	4457.9	701.1	157
	GDD (tenths deg Celsius)	2000-2019	139.6	787.5	597.4	4554.4	656.6	151
Normal event	GDD (tenths deg Celsius)	1971-2019	51.29	311.02	229.85	1171.66	214.4	242
	GDD (tenths deg Celsius)	1971-1990	63.33	289.34	187.91	804.24	180.29	100
	GDD (tenths deg Celsius)	2000-2019	51.29	300.73	173.94	1147.37	221.53	96
Wet spell	EDD (tenths deg Celsius)	1971-2019	0.000	0.710	0.042	13.338	1.790	351
	EDD (tenths deg Celsius)	1971-1990	0.000	0.536	0.026	13.338	1.572	140
	EDD (tenths deg Celsius)	2000-2019	0.000	0.943	0.101	12.2654	2.118	151
Dry spell	EDD (tenths deg Celsius)	1971-2019	0.000	1.506	0.037	55.210	4.626	368
	EDD (tenths deg Celsius)	1971-1990	0.000	1.883	0.064	55.210	5.464	157
	EDD (tenths deg Celsius)	2000-2019	0.000	1.389	0.031	39.739	4.284	151
Normal event	EDD (tenths deg Celsius)	1971-2019	0.000	0.364	0.000	8.058	1.030	242
	EDD (tenths deg Celsius)	1971-1990	0.000	0.414	0.008	5.990	1.079	100
	EDD (tenths deg Celsius)	2000-2019	0.000	0.400	0.000	8.058	1.163	96

Note: a wet (dry) spell event is defined as two or more consecutive days with daily rain above (below) 30 tenths of mm. Normal events are formed by days that do not belong in a wet or dry event.

Table A.6: Regressions of county crop yields on monthly rain and temperature.

	Corn yield (bu/acre) (1971-2019)	Soybean yield (bu/acre) (1971-2019)
R_{june}	0.0140***	0.0017***
	(0.0008)	(0.0002)
R^2_{june}	-0.000005***	-0.0000007***
	(0.0000003)	(0.00000007)
R_{july}	0.0187***	0.0033***
	(0.0009)	(0.0002)
R^2_{july}	-0.000004***	-0.0000008***
	(0.0000003)	(0.00000007)
R_{august}	0.0092***	0.0061***
	(0.0006)	(0.0002)
R^2_{august}	-0.000003***	-0.000002***
	(0.0000002)	(0.00000002)
GDD_{june}	0.0009*	0.0003***
	(0.0004)	(0.0001)
GDD_{july}	0.0009***	0.0004***
	(0.0003)	(0.0001)
GDD_{august}	-0.0026***	-0.0006***
	(0.0002)	(0.00007)
EDD_{june}	0.0313	0.0299***
	(0.0360)	(0.0083)
EDD_{july}	-0.1171***	-0.0222***
	(0.0131)	(0.0023)
EDD_{august}	-0.0009	-0.0061***
	(0.0139)	(0.0023)
$R_{june} \times EDD_{june}$	0.00002	-0.00006***
	(0.00007)	(0.00001)
$R_{july} \times EDD_{july}$	-0.00007***	0.000002
	(0.00002)	(0.000003)
$R_{august} \times EDD_{august}$	-0.00010***	0.00001**
	(0.00002)	(0.000004)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	40,150	39,427
R^2	0.848	0.827
Within R^2	0.161	0.161

Notes: Daily rain, growing degree days (GDD) and extreme degree days (EDD) are summed up over each month for each county in the U.S. Midwest. Observations are weighted by crop acreage. Standard errors in parentheses were clustered at the county level, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.7: Regressions of crop percentage price changes on contemporaneous weather event rain and temperature variables (1971-2019).

	Corn return (%)			Soybean return (%)		
	Piecewise Quadratic	Piecewise Linear	Splines	Piecewise Quadratic	Piecewise Linear	Splines
Const.	0.0709	0.1018	0.8617	−0.0436	−0.0137	4.4763**
	(0.2926)	(0.2827)	(1.3681)	(0.2848)	(0.2565)	(1.8171)
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)>0\right]\times W$	0.00017***			0.00015***		
	(0.00003)			(0.00003)		
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)<0\right]\times W$	0.00001*			0.00001***		
	(0.00001)			(0.000004)		
$(R-R^*).\mathbb{1}\left[(R-R^*)>0\right]\times W$		0.0348***			0.0339***	
		(0.0102)			(0.0069)	
$(R-R^*).\mathbb{1}\left[(R-R^*)<0\right]\times W$		−0.0083***			−0.0098***	
		(0.0024)			(0.0021)	
$Spline(R-R^*)1\times W$			−0.788			−5.032**
			(1.535)			(2.071)
$Spline(R-R^*)2\times W$			0.266			−4.235**
			(1.619)			(2.093)
$Spline(R-R^*)3\times W$			−6.369***			−7.202***
			(1.541)			(1.581)
$Spline(R-R^*)4\times W$			12.142***			4.782
			(3.423)			(4.120)
$Spline(R-R^*)5\times W$			16.047***			9.124***
			(2.818)			(2.098)
$GDD\times W$	−0.00283	−0.00301*	−0.00223	−0.00112	−0.00100	0.00019
	(0.00174)	(0.00173)	(0.00197)	(0.00114)	(0.00113)	(0.00133)
$EDD\times W$	−0.10045	−0.11369	−0.20747*	0.03786	−0.00586	−0.09198
	(0.11267)	(0.10420)	(0.10832)	(0.10552)	(0.09208)	(0.09293)
$EDD\times(R-R^*)\times W$	−0.00099***	−0.00103***	−0.00124***	−0.00028	−0.00039*	−0.00055**
	(0.00028)	(0.00022)	(0.00022)	(0.00027)	(0.00022)	(0.00022)
FX	5.04	10.53	13.87	−27.66*	−21.62	−15.67
	(17.15)	(17.63)	(17.86)	(16.34)	(16.06)	(16.36)
$Length$	0.191	−0.003	−0.062	0.037	−0.228	−0.368**
	(0.214)	(0.229)	(0.240)	(0.158)	(0.171)	(0.182)
$Length^2$	−0.0039	0.0060	0.0080	−0.0022	0.0094	0.0118**
	(0.0073)	(0.0079)	(0.0061)	(0.0076)	(0.0069)	(0.0053)
Observations	961	961	961	959	959	959
Adjusted R^2	0.240	0.236	0.242	0.160	0.163	0.167

Notes: The sample is all weather events in 1971-2019. R, GDD and EDD are event rain, Growing Degree Days and Extreme Degree days over the duration the event and after spatial averaging over the U.S. Midwest. R^* is the estimated amount of monthly rain that maximizes crop yield (1,714 and 1,729 tenths of a mm for corn and soybeans, respectively), linearly scaled by $Length$ which is the duration of the weather event in days. W is the relative weight of U.S. Midwest crop output in U.S. crop output. FX is the contemporaneous return of the U.S. dollar relative to a basket of international currencies. Spline terms are natural cubic splines with 5 knots placed at quantiles of $(R-R^*)$ values. HAC or HC standard errors in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.8: Regressions of crop percentage price changes on contemporaneous weekly rain and temperature variables (1971-2019).

	Corn return (%) (1971-2019)	Soybean return (%) (1971-2019)
Const.	1.249**	1.782***
	(0.599)	(0.548)
$R \times W$	−0.030***	−0.039***
	(0.008)	(0.007)
$R^2 \times W$	0.00006***	0.00008***
	(0.00002)	(0.00002)
$GDD \times W$	0.0007	0.0014*
	(0.0008)	(0.0008)
$EDD \times W$	0.426**	0.315**
	(0.166)	(0.127)
$EDD \times R \times W$	−0.0024*	−0.0025**
	(0.0013)	(0.0011)
FX	−12.210	−23.943
	(20.644)	(20.977)
Observations	672	672
Adjusted R^2	0.051	0.063

Notes: The sample is all weeks in June-August, 1971-2019. R, GDD and EDD are weekly rain, Growing Degree Days and Extreme Degree Days after spatial averaging over the U.S. Midwest. W is the relative weight of U.S. Midwest output in U.S. output. FX is the contemporaneous return of the U.S. dollar relative to a basket of international currencies. HAC or HC standard errors in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.9: Regressions of CME wheat percentage price changes on contemporaneous weather event rain and temperature variables for various time periods.

	Wheat return (%)		
	(1971-2019)	(1971-1990)	(2000-2019)
Const.	0.539**	0.101	0.874**
	(0.250)	(0.309)	(0.432)
R	−0.00243	0.00459	−0.00242
	(0.00249)	(0.00435)	(0.00631)
R^2	0.0000003	−0.00001	−0.000001
	(0.000003)	(0.00001)	(0.00001)
GDD	0.00198	0.00032	0.00331
	(0.00123)	(0.00155)	(0.00209)
EDD	0.0836	−0.0513	0.2226
	(0.0948)	(0.0841)	(0.1626)
$R \times EDD$	−0.00019	0.00030	−0.00078
	(0.00063)	(0.00075)	(0.00108)
FX	−41.75**	34.95*	−71.82***
	(18.96)	(18.36)	(27.01)
BDI			−6.99*
			(4.18)
WTI			14.91**
			(6.48)
$Length$	−0.4403**	−0.1191	−0.8205***
	(0.2036)	(0.2536)	(0.3163)
$Length^2$	0.01206*	0.00506	0.02301**
	(0.00680)	(0.00574)	(0.00982)
Observations	961	397	398
Adjusted R^2	0.0401	0.0030	0.1451

Notes: The sample is all weather events in June, July and August within each time period. R, GDD and EDD are event rain, Growing Degree Days and Extreme Degree Days over the duration the event and after spatial averaging over the U.S. Midwest. $Length$ is the duration of the weather event in days. FX is the contemporaneous return of the U.S. dollar relative to a basket of international currencies. BDI and WTI are contemporaneous returns in the Baltic Dry Index and the WTI oil price. HAC or HC standard errors in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.10: Regressions of county crop yields on county monthly rain and temperature for various time periods.

	Corn yield (bu/acre)		Soybean yield (bu/acre)	
	(1971-1990)	(2000-2019)	(1971-1990)	(2000-2019)
R_{june}	0.0122***	0.0168***	0.0005	0.0029***
	(0.0010)	(0.0012)	(0.0003)	(0.0003)
R^2_{june}	-4.02×10^{-6}***	-5.66×10^{-6}***	-3.69×10^{-7}***	-8.8×10^{-7}***
	(3.7×10^{-7})	(4.24×10^{-7})	(1.08×10^{-7})	(8.64×10^{-8})
R_{july}	0.0246***	0.0255***	0.0047***	0.0058***
	(0.0010)	(0.0013)	(0.0003)	(0.0003)
R^2_{july}	-6.47×10^{-6}***	-7.03×10^{-6}***	-1.2×10^{-6}***	-1.79×10^{-6}***
	(3.62×10^{-7})	(4.39×10^{-7})	(1×10^{-7})	(1.23×10^{-7})
R_{august}	0.0088***	0.0104***	0.0054***	0.0069***
	(0.0009)	(0.0009)	(0.0002)	(0.0003)
R^2_{august}	-2.58×10^{-6}***	-2.45×10^{-6}***	-1.49×10^{-6}***	-1.59×10^{-6}***
	(3.49×10^{-7})	(3.07×10^{-7})	(8.12×10^{-8})	(1.2×10^{-7})
GDD_{june}	0.0028***	0.0017**	0.0006***	0.0003**
	(0.0004)	(0.0007)	(0.0001)	(0.0001)
GDD_{july}	-0.0030***	0.0012*	-0.0005***	0.0006***
	(0.0004)	(0.0006)	(0.0001)	(0.0001)
GDD_{august}	-0.0004	-0.0028***	0.0001	-0.0009***
	(0.0003)	(0.0004)	(0.0001)	(0.0001)
EDD_{june}	0.1779***	-0.0867	0.0451***	0.0220
	(0.0279)	(0.0938)	(0.0124)	(0.0168)
EDD_{july}	-0.0560***	-0.1927***	-0.0121***	-0.0423***
	(0.0118)	(0.0294)	(0.0018)	(0.0067)
EDD_{august}	-0.0815***	0.1241***	-0.0548***	-0.0435***
	(0.0248)	(0.0239)	(0.0062)	(0.0076)
$R_{june} \times EDD_{june}$	0.0001**	0.0002	-2.83×10^{-6}	-7.36×10^{-5}***
	(5.65×10^{-5})	(0.0001)	(2.03×10^{-5})	(2.01×10^{-5})
$R_{july} \times EDD_{july}$	-0.0001***	-5.32×10^{-5}	2.36×10^{-6}	1.57×10^{-5}
	(2.56×10^{-5})	(4.04×10^{-5})	(4.04×10^{-6})	(9.67×10^{-6})
$R_{august} \times EDD_{august}$	-0.0001***	-0.0001***	1.3×10^{-5}**	3.02×10^{-6}
	(2.84×10^{-5})	(2.19×10^{-5})	(6.64×10^{-6})	(6.33×10^{-6})
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,627	15,595	15,910	15,595
R^2	0.823	0.778	0.781	0.825
Within R^2	0.254	0.198	0.193	0.228

Notes: Daily rain, growing degree days (GDD) and extreme degree days (EDD) are summed up over each month for each county in the U.S. Midwest. Observations are weighted by crop acreage. Standard errors in parentheses were clustered at the county level, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.11: Regressions of crop returns on contemporaneous weather event rain and temperature variables for various periods. Optimal rain estimated from yields in 1971-2019.

	Corn return (%)		Soybean return (%)	
	(1971-1990)	(2000-2019)	(1971-1990)	(2000-2019)
Const.	0.023	0.219	−0.473	0.275
	(0.349)	(0.375)	(0.365)	(0.332)
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)>0\right]\times W$	0.0002	0.0002***	0.0001	0.0001***
	(0.0001)	(0.00002)	(0.0001)	(0.00001)
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)<0\right]\times W$	0.00001	0.00002***	0.00002***	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00000)
$GDD\times W$	−0.0004	−0.002	0.001	−0.0002
	(0.002)	(0.002)	(0.003)	(0.002)
$EDD\times W$	−0.692***	0.028	−0.133	−0.026
	(0.221)	(0.115)	(0.197)	(0.088)
$EDD\times(R-R^*)\times W$	−0.002***	−0.001***	−0.001**	0.00002
	(0.0005)	(0.0002)	(0.0004)	(0.0002)
FX	44.35*	−23.43	14.69	−57.16***
	(24.32)	(23.56)	(28.42)	(20.52)
BDI		−0.370		−0.113
		(3.400)		(3.024)
WTI		4.431		10.800**
		(4.800)		(4.493)
$Length$	0.062	0.004	0.114	−0.192
	(0.209)	(0.274)	(0.303)	(0.230)
$Length^2$	−0.011	−0.011	−0.030**	−0.001
	(0.012)	(0.013)	(0.012)	(0.011)
Observations	397	398	395	398
Adjusted R^2	0.262	0.331	0.162	0.292

Notes: R, GDD and EDD are event rain, Growing Degree Days and Extreme Degree days over the duration the event and after spatial averaging over the U.S. Midwest. R^* is the estimated amount of monthly rain that maximizes crop yield (1,714 and 1,729 tenths of a mm for corn and soybeans, respectively), linearly scaled by $Length$ which is the duration of the weather event in days. W is the relative weight of U.S. Midwest crop output in U.S. crop output. FX is the contemporaneous return of the U.S. dollar relative to a basket of international currencies. BDI and WTI are the contemporaneous returns of the Baltic Dry Index and the WTI oil price. HAC or HC standard errors in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

Table A.12: Regressions of crop returns on weather event rain and temperature variables for various periods. Optimal rain estimated from yields in each period.

	Corn return (%)		Soybean return (%)	
	(1971-1990)	(2000-2019)	(1971-1990)	(2000-2019)
Const.	0.020	0.209	−0.451	0.267
	(0.349)	(0.373)	(0.362)	(0.330)
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)>0\right]\times W$	0.0002	0.0002***	0.00004	0.0002***
	(0.0001)	(0.00003)	(0.00004)	(0.00001)
$(R-R^*)^2.\mathbb{1}\left[(R-R^*)<0\right]\times W$	0.00001	0.00002***	0.00003***	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00000)
$GDD\times W$	−0.0005	−0.002	0.0005	−0.0001
	(0.002)	(0.002)	(0.003)	(0.002)
$EDD\times W$	−0.672***	0.019	−0.089	−0.032
	(0.219)	(0.115)	(0.189)	(0.089)
$EDD\times(R-R^*)\times W$	−0.002***	−0.001***	−0.001*	0.00001
	(0.001)	(0.0002)	(0.001)	(0.0002)
FX	44.20*	−24.10	13.99	−58.05***
	(24.31)	(23.59)	(28.42)	(20.62)
BDI		−0.514		−0.286
		(3.416)		(3.059)
WTI		4.894		11.352**
		(4.784)		(4.414)
$Length$	0.071	0.009	0.108	−0.193
	(0.209)	(0.273)	(0.303)	(0.230)
$Length^2$	−0.012	−0.010	−0.029**	−0.0002
	(0.012)	(0.013)	(0.012)	(0.011)
Observations	397	398	395	398
Adjusted R^2	0.263	0.331	0.165	0.293

Notes: R, GDD and EDD are event rain, Growing Degree Days and Extreme Degree days over the duration the event and after spatial averaging over the U.S. Midwest. R^* is the estimated amount of monthly rain that maximizes crop yield within each period (1,655 and 1,472 tenths of a mm for corn and soybeans in the first period, and 1,774 and 1,809 in the second period), linearly scaled by $Length$ which is the duration of the weather event in days. W is the relative weight of U.S. Midwest crop output in U.S. crop output. FX is the contemporaneous return of the U.S. dollar relative to a basket of international currencies. BDI and WTI are the contemporaneous returns of the Baltic Dry Index and the WTI oil price. HAC or HC standard errors in parentheses, *p< 0.1; **p< 0.05; ***p< 0.01.

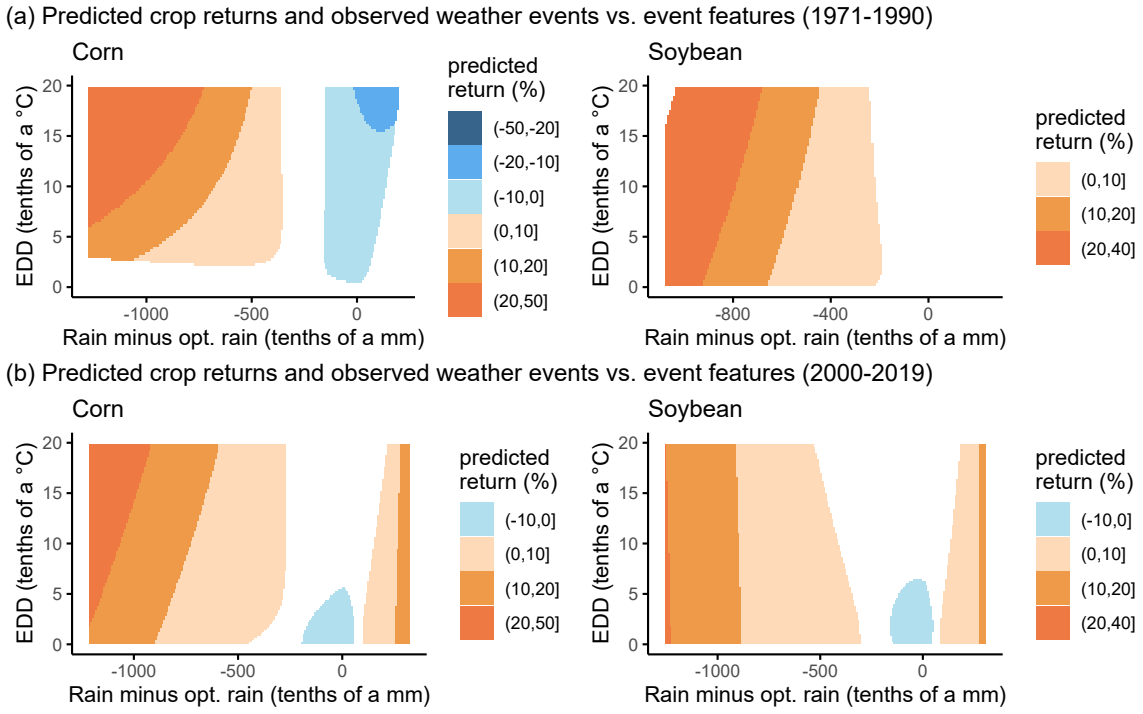


Figure B.2: Figures (a) and (b) display predicted market returns as a function of precipitation deviations and EDD where the optimal precipitation is estimated from table A.12 and separately for each period. This is a robustness exercise for figure 3 in which optimal precipitation is constant across periods. Shown in color are predicted values that are statistically different from zero at the 5% significance level.