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Substitution of Human and Physical Capitals in Farm Adaptation to Extreme Temperatures: Evidence from Corn Yields in US

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Abstract

This study delves into the factors that underly farmer's adaptation of farm production to extreme weather. Specifically, we examine how farmer's age mitigates the negative effects of extreme temperatures on crop yields. Our findings reveal a nonlinear relationship between age and the ability to adapt, wherein the adaptation capability generally increases and then decreases with age. Furthermore, we explore how farmer's age interacts with farm technology, such as irrigation, to influence farmer's adaptation simultaneously. Interestingly, age effects are less pronounced in irrigated areas, where the likelihood of exposure to climate risk is comparably low. This suggests that human capital plays a critical role in introducing adaptation measures in areas at high risk of exposure to extreme temperatures.

Keywords: Adaptation, Adaptation capability, Climate change, Corn, Crops yields, Extreme temperatures, Farmer's age, Irrigation
JEL classification: Q10, Q51, Q54

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I. Introduction

Crop production has been at risk from climate change. Existing literature indicates that crops are susceptible to extreme heat, and temperature rise is likely to reduce crop yields (e.g., Schlenker and Roberts 2009; Burke and Emerick 2016; Chen et al. 2016). Farmers can adapt to mitigate yield loss by such as installing irrigation, changing planting dates, and developing new heat–tolerant seed varieties, but the degree to adapt depends on farmers' ability and available farm technology.

This study examines how farmers' ability and farm technology influence the adaptation capability of farm production to extreme weather events. It has not been fully explored what type of farmers are more likely to adapt and reduce extreme temperature effects on crop yields.[1] We specifically investigate how farmers' age and irrigation use reduce the negative effects of extreme temperatures on crop yields.

Aging lowers cognitive and physical skills that could augment productivity (Tauer 1984; Maestas et al. 2016; Eggertsson et al. 2019; Lee and Shin 2019; Park et al. 2021). Aging also functions as a barrier to the adoption of new climate–resilient technologies, because new technologies are too complex (Park 2000; Salthouse et al. 2003; Salthouse 2012; Klein et al. 2015; Hunter et al. 2016) or near–retirement farmers are less likely to invest in them (Czaja and Sharit 1998; Barnes et al. 2019; Shang et al. 2021). On the other hand, aging has a positive aspect on production as farmers accumulate more experiences and knowledge from learning–by–doing. Tauer (1984) found an inverted U–shape relationship between agricultural productivity and farmer's age, which can be led by these relative merits and demerits of aging. We hypothesize that farmer's age has a similar nonlinear effect on crop yields under the risk of extreme temperatures.

We further explore how the farmer's ability and the farm technology influence the adaptation capability simultaneously. Irrigation technology can relieve heat stress by cooling the canopy temperature (Siebert et al. 2014) and thereby control a resilient environment to alleviate negative temperature effects (e.g., Troy et al. 2015; Tack et al. 2017; Zaveri and Lobell 2019). Such physical capital may be able to complement human capital decay by aging. In other words, we postulate that a decline in the degree of adaptation to extreme temperatures due to farmer's aging can be reinforced by the

[1] Many studied the determinants of adaptation to climate change. Kgosikoma et al. (2018) found that farmers' gender, age, household size, poverty, and knowledge about climate change significantly influence their adaptation. Apart from the above, level of education, access to extension and credit, and membership to farmers' groups are also found to determine farmers' choices (Deressa et al. 2009; Shikuku et al 2017). However, it is unclear whether such determinants help farmers mitigate the negative impacts of climate change.

presence of irrigation technology. To the best of our knowledge, this represents the first systematic attempt to understand the collective influence of farmer age and irrigation technology on crop yield resilience in the face of climate challenges.

We test our hypotheses by using US corn yield data from 2002 to 2017. Corn is one of the primary cereal grains in the world,[2] and is the most widely produced feed grain in the United States.[3] Corn is susceptible to heat stress and drought. Under the global warming scenario, corn yields will significantly decline across the world (IPCC 2022). Adaptation to the warming scenario is urged to mitigate such a negative warming effect, and enhancing the degree of adaptation is a key to facilitate adaptation.

Figure 1 plots annual county–average corn yields in natural logarithm and farmer's age in irrigated and rainfed (non–irrigated) areas in US corn–producing counties. The distribution of age appears similar across the irrigated and rainfed counties. We also observe an inverted U–shape relationship between age and corn yields in both irrigated and rainfed counties. We test that this relationship comes through which age affects farmer's adaptation capability that mitigates the negative temperature effect on corn yields. In addition, the curvature of the U–shape fitting is different between irrigated and rainfed counties. This difference can indicate that the negative aging effect on the yield–temperature relationship is offset by irrigation technology.

Aging is inevitable in modern society. Figure 2 shows the dynamics of American corn farmer's age in our sample period. The average age of farmers has increased from 52.2 to 54.4 years old over the decade. The negative aging effect on the yield–temperature relationship in Figure 1 likely becomes larger in recent years. Revealing the effect of adaptation capability to a temperature rise is important to prevent further potential damages from global warming and aging.

We find that age nonlinearly influences farmer's adaptation capability to reduce the negative temperature effect: Capability generally increases and then decreases with age (inverted U–shaped age effects). Interestingly, age effects are smaller in irrigated areas where exposure to climate risk is relatively low. This suggests that human capital plays a critical role in introducing adaptation measures in areas at high risk of exposure to

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[2] According to OECD-FAO Agricultural Outlook 2019–2028 (https://www.oecd-ilibrary.org/agriculture-and-food/oecd-fao-agricultural-outlook-2019-2028_agr_outlook-2019-en), corn is the most widely used cereal in both developed and developing countries, with the largest growth in area and yield worldwide. In addition, US is the largest corn producer and a major player in the global corn trade market, exporting 10–20 percent of its annual production. See USDA Foreign Agricultural Service (FAS) U.S. Corn Exports in 2021 for more detailed information (https://www.fas.usda.gov/commodities/corn).

[3] Corn accounts for more than 95 percent of total feed grain production in US. It is also used for livestock feed and industrial products such as fuel ethanol. See United States Department of Agricultural (USDA) National Agricultural Statistics Service (NASS) Statistics by Subject for detailed information (https://www.nass.usda.gov/Statistics_by_Subject/index.php?sector=CROPS).

extreme temperatures.

The remainder of this paper is organized with the delineation of empirical methodology and data in Section ll and the discussion of estimation results in Section lll. Section IV concludes.

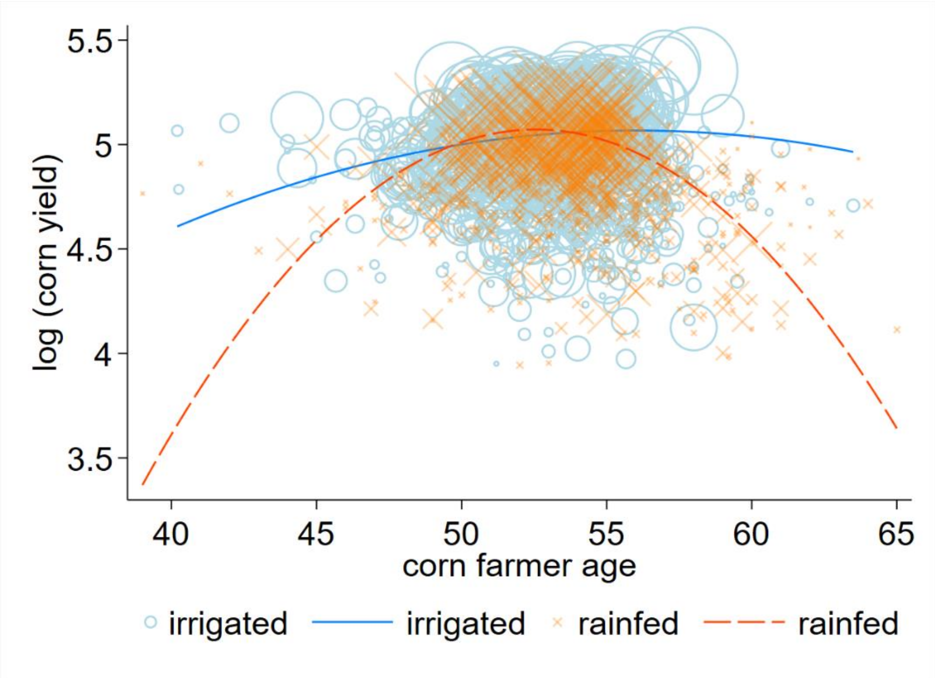

Figure 1: County average corn yields and farmer's age by irrigated and rainfed areas in US corn production counties over 2002–2017

Notes: We draw a quadratic fit on county average corn yields and farmer's age over 2002–2017 with the weight of average corn acreage over the same period. They are obtained respectively from Schlenker and Roberts (2009) and US Agricultural Censuses. See the data section for a detailed description.

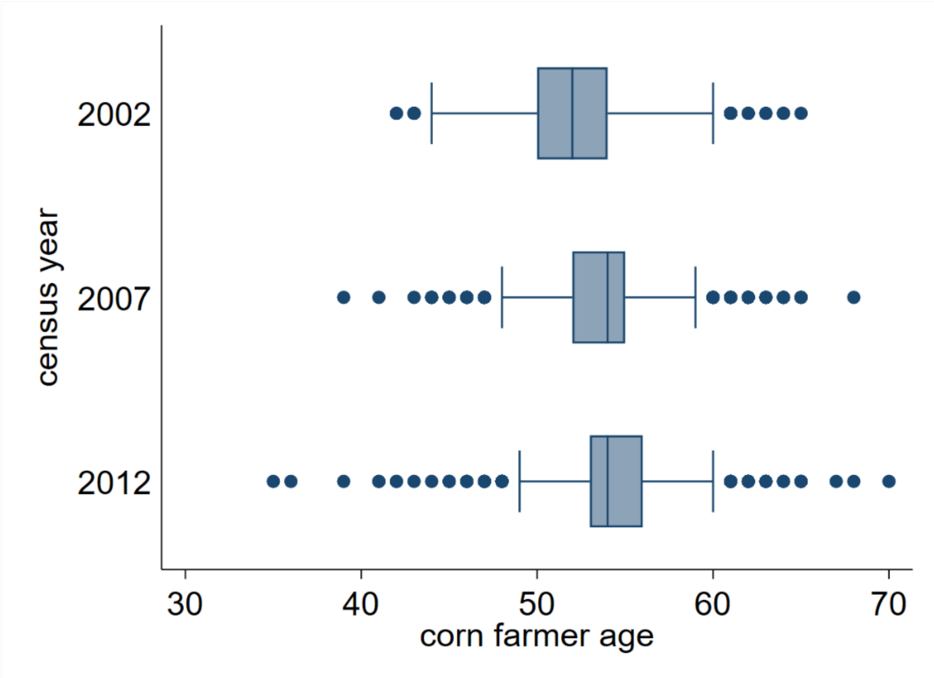

Figure 2: Farmer's age dynamics over Agricultural Census years

Notes: Annual county–average corn farmer's age is attained from US Agricultural Censuses 2002–2012.[4] See the data section for a detailed description.

II. Methodology and Data

A. Methodology

We start to delineate the yield response function to temperatures by following Burke and Emerick (2016) who used the panel analysis and GDD (growing degree days) method to estimate the yield–temperature relationship. Temperature effects on crop yields are often measured by GDD in the literature. GDD accounts for the cumulative heat that crops receive over the growing season. To further account for the nonlinear yield–temperature relationship, Burke and Emerick (2016) construct $\text{GDD}_{\leq T}$ which measures cumulative heat between the lower and upper bound daily temperature threshold, T, where the lower and upper bound thresholds are set as 0°C and 28°C, respectively. Similarly, $\text{GDD}_{>T}$

[4] Considering that farmer characteristics are predominant in affecting adaptation behaviors, the current census year data is matched to yield and weather data for the following 5 years. For example, census year data for 2012 is matched to yield and weather data for 2013–2017.

measures the cumulative heat above T over the growing season.[5] To examine the effect of farmer's age on the yield–temperature relationship, we test our hypotheses by introducing interaction terms of these GDD variables with the measure of farmer's adaptation ability (farmer's age) in the models described below.

The effect of temperatures and adaptation measures is estimated by the panel approach as given by:

$$\log(\mathrm{Y}_{it}) = \alpha_0 + \beta_1 \mathrm{GDD}_{\leq T\,it} + \beta_2\left(\mathrm{GDD}_{\leq T\,it} \times \mathrm{X}_{it}\right) + \beta_3 \mathrm{GDD}_{>T\,it}$$

$$+\beta_4\left(\mathrm{GDD}_{>T\,it} \times \mathrm{X}_{it}\right) + \delta \mathrm{X}_{it} + \mathbf{Z}_{it}\gamma + \mathrm{C}_i + \lambda_{st} + \varepsilon_{it}, \tag{1}$$

where Y_{it} is corn yield in county i in year t, X_{it} represents farmer's age, a vector $\mathbf{Z}_{it}$ includes the other explanatory variables of precipitation[6] and farm characteristics (irrigation use, farmer's age, and farm size), the county fixed effects C_i account for county–specific confounding factors such as geological conditions, the state by year fixed effects λ_{st} account for technological change and policy interventions, and ε_{it} indicates the error term.

B. Data

Agricultural data on corn acreage and yields and weather data on temperatures and precipitation are drawn from Schlenker and Roberts (2009).[7] Farm characteristics data such as corn acreage for irrigation, number of corn farms, etc. is obtained from US Agricultural Censuses via Inter–university Consortium for Political and Social Research collection. Additionally, age data for corn farmers is obtained through a special request

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[5] For example, if $T = 19$ and a set of daily temperatures is -1, 15, 18, 21, and 24, $\mathrm{GDD}_{\leq T}$ is equal to 0, 15, 18, 19, and 19, and $\mathrm{GDD}_{>T}$ is equal to 0, 0, 0, 2, and 5.

[6] Following Burke and Emerick (2016), we set the growing season threshold precipitation at 50cm. A below-threshold precipitation variable is constructed by taking the difference between the cumulative precipitation for the growing season and the threshold precipitation for the growing season interacted with an indicator variable for precipitation being below the threshold. An above-threshold precipitation variable is constructed similarly. Their cross terms with the adaptation ability measure are also included in $\mathbf{Z}_{\mathrm{it}}$.

[7] The agricultural data used in Schlenker and Roberts (2009) is from United States Department of Agriculture (USDA). The USDA's National Agricultural Statistics Service (NASS) provides annual data on corn acreage and yields at the county level. The weather data is also drawn from Schlenker and Roberts (2009) and include daily interpolated values of precipitation totals and maximum and minimum temperatures for 4 km grid cells covering the entire United States. These weather data are aggregated to the county-day level by averaging daily values for grid cells in each crop-growing county, which are estimated from satellite data.

process.[8] Following the previous literature, our analysis focuses on counties east of the 100th meridian and on weather conditions in the growing season from April to September.

Figures 3 and 4 display the spatial distribution of county average corn yields and average corn farmer's age over the study period in Figure 1, respectively. We notice that counties with lower yields are located primarily in warmer regions in the southern US. The distribution of corn yields seems negatively associated with that of the average corn farmer's age. This indicates that corn yields are lower in a warmer climate where more older farmers involve in corn production. In contrast, the spatial distribution of the average share of land irrigated for corn production does not seem associated with that of corn yields or corn farmer's age (Figure 5). Corn production is highly irrigated, particularly in the western and southeastern US including Arkansas, Louisiana, Tennessee, southern Georgia, and central Florida, where corn yields are high while corn farmer's age is also in the high range. We use this variation to evaluate the irrigation effect on the relationship between age, extreme temperatures, and yields.

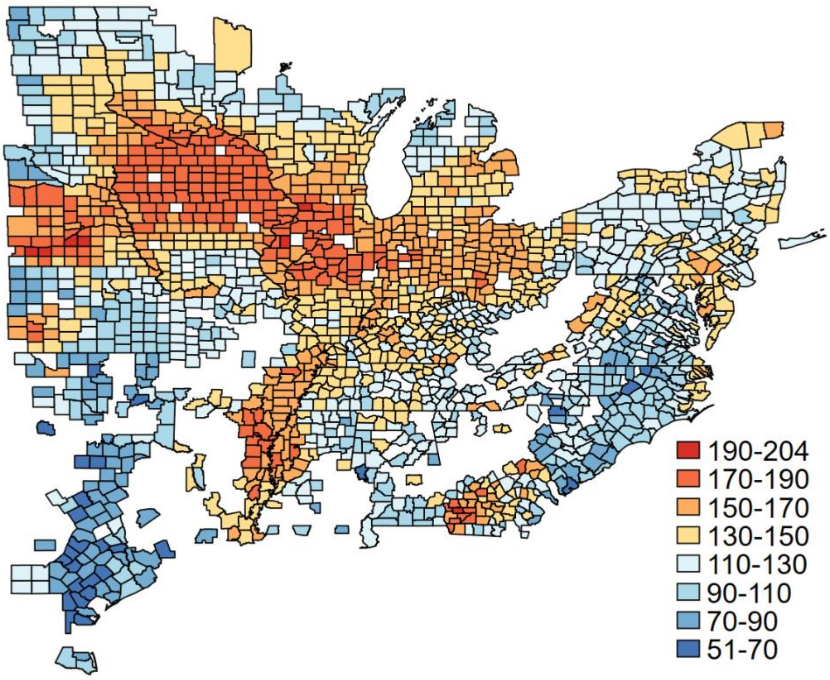

Figure 3. County average corn yield (bushels/acre) over 2002–2017

Notes: Data are for US counties east of the 100th meridian.

[8] We would like to express our gratitude to the Data Lab of the USDA's NASS for generously providing the age data used in this study. Their assistance was invaluable in enhancing the quality and depth of our research.

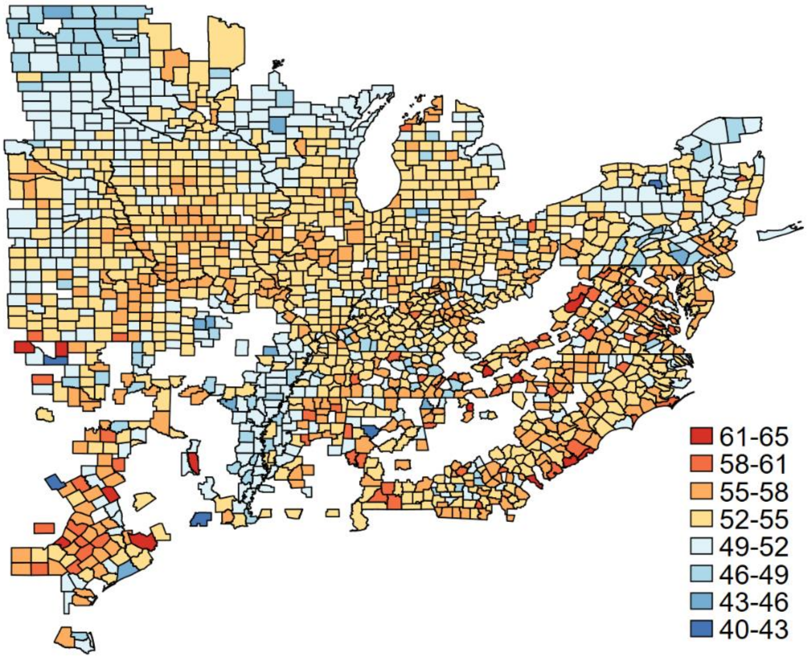

Figure 4. County average corn farmer age (years old) over 2002–2017

Notes: See Notes in Figure 3.

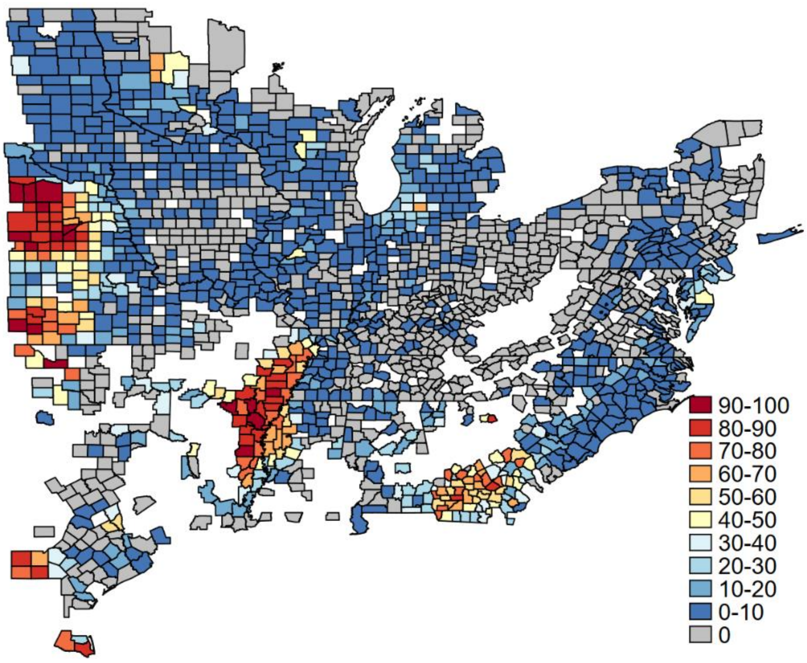

Figure 5. County average share of land irrigated for corn production (%) over 2002–2017

Notes: See Notes in Figure 3.

III. Empirical Results

A. Yield–Temperature Response Function

We first provide results from estimating the yield response function to temperatures. Columns 1–4 produce results using temperature, precipitation, and other control variables (share of corn farmers under age 35, share of corn farmers over age 65, share of corn irrigated land, and corn farm size) with different fixed effects (county and year fixed effects, county and state by year fixed effects, county fixed effect and state–specific quadratic year trend, and county fixed effect and county–specific quadratic year trend, respectively). Results show very similar parameter estimates of the responsiveness of corn yields to temperatures.[9,10]

We find that corn yields respond positively to temperatures below the threshold of 28°C and negatively to temperatures above the threshold. Our preferred specification of the panel model in column (2) shows that exposure to an additional degree day below the threshold yields a marginal increase in corn yields by 0.01 percent, albeit insignificantly, while exposure to an additional degree day above the threshold results in a decrease in corn yields by 0.55 percent. Consistent with Burke and Emerick (2016), these results indicate that US corn yields are particularly vulnerable to high temperatures. Figure 6 displays the yield–temperature response function in column (2) with the 95 percent confidence intervals.

We also estimate heterogeneous temperature effects on corn yields in irrigated and rainfed counties. We assign counties with no irrigation use in 2002–2017 as rainfed counties, and irrigated counties otherwise. We further classify irrigated counties into high-irrigation and low-irrigation categories based on the 75th percentile. The yield–temperature response functions parallel to Figure 6 are depicted in Figure 7 (and parameter estimates are provided in Appendix Table A4). We find in rainfed counties that the corn yields appear more vulnerable to hot temperatures (with a steeper slope).

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9 Appendix Table A2 shows that the results are consistent regardless of whether other control variables are included.

10 The reduced number of observations is attributed to the availability of data on farm characteristics. In Appendix Table A3, we present evidence to indicate that the absence of census data does not have any significant bearing on the results obtained from our analysis.

Table 1. Results of the nonlinear temperature effects on corn yields

	(1)	(2)	(3)	(4)
GDD below threshold	0.0002	0.0001	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDD above threshold	-0.0046***	-0.0055***	-0.0047***	-0.0046***
	(0.0006)	(0.0009)	(0.0005)	(0.0005)
Precip below threshold	0.0009	0.0029*	0.0041*	0.0039*
	(0.0021)	(0.0015)	(0.0021)	(0.0023)
Precip above threshold	-0.0016**	-0.0013**	-0.0014**	-0.0013**
	(0.0007)	(0.0005)	(0.0006)	(0.0006)
Observations	16,985	16,985	16,985	16,985
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	Yes	Yes	Yes	Yes
Adjusted R^2	0.7128	0.8110	0.7014	0.6823

Notes: ***, **, and * denote 1 percent, 5 percent, and 10 percent significant levels, respectively. Specifications are estimated with different fixed effects shown at the bottom; see main text for details. Data are for US counties east of the 100th meridian, 2002–2017. Standard errors clustered at the state level are reported in parentheses. Regressions are weighted by the 2002–2017 average corn area. Observations are dropped due to singleton observations.

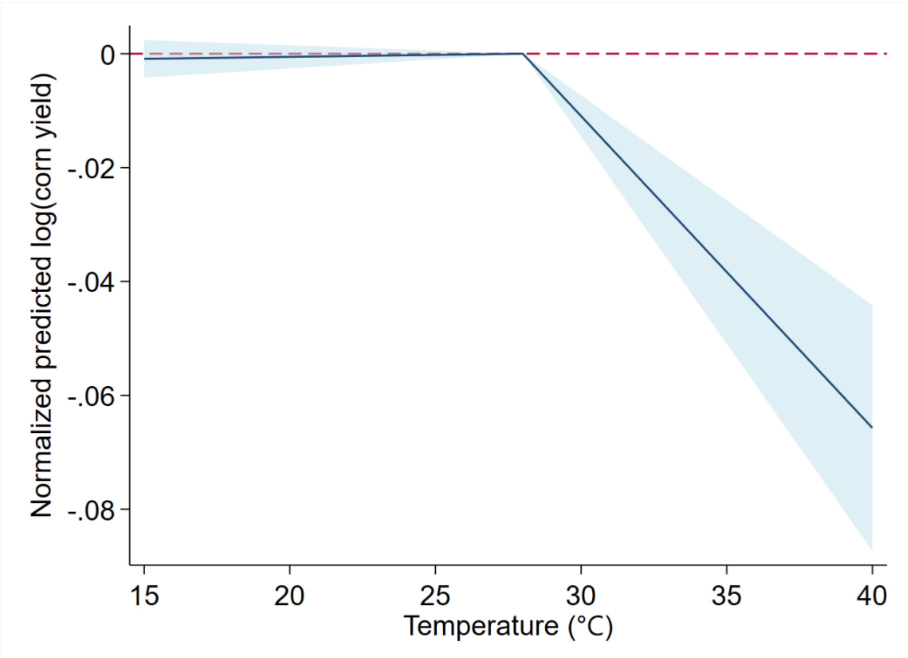

Figure 6. Corn yield response function to temperatures

Notes: Parameter estimates in Table 1 are converted to the marginal change in log corn yields with respect to a day of exposure to a given °C temperature relative to a day spent at a threshold temperature of 28°C. The solid line represents the yield–temperature response function. The shaded area represents 95 percent confidence intervals.

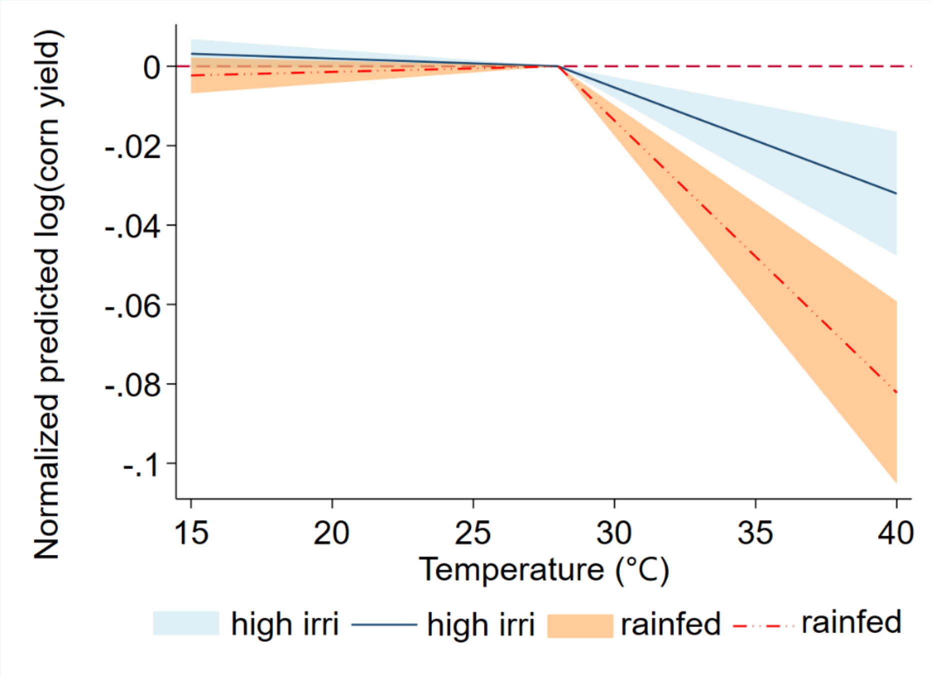

Figure 7. Corn yield response function to temperatures in irrigated vs. rainfed counties

Notes: Corn yield response function to temperatures in Figure 6 is estimated separately in irrigated (categorized into high irrigation and low irrigation) and rainfed counties. Indicator variables representing zero and nonzero irrigated share of corn acreage (classified into high irrigation and low irrigation) are interacted with all explanatory variables. In the visualization, we exclusively present the results for high irrigated and rainfed counties. The sensitivity of crop yield to temperatures in low irrigated counties falls between that of high irrigated and rainfed counties. Table point estimates are provided in Appendix Table A4, while graphical results for low irrigated counties can be obtained upon request.

B. *Farmer's Adaptation, Farmer's Adaptation Ability and the Yield–Temperature Relationship*

Farmer's adaptation is important to mitigate the negative temperature effects on crop yields. As an example, high irrigation utilization likely mitigates the negative effects of hot temperatures on crop yields (e.g., Troy et al. 2015; Tack et al. 2017; Zaveri and Lobell 2019). To ensure that our results are consistent with the existing literature (since we use a different timeline), we perform the same hypothesis tests on corn yields.

Table 2 presents the results for the effect of irrigation on the yield–temperature relationship, where we use the share of irrigated corn acreage over total corn acreage.

Consistent with the previous studies mentioned above, irrigation usage reduces the negative temperature effects on corn yields. A parameter estimate of GDD above the threshold (-0.0067) indicates that exposure to an additional degree day above the threshold significantly decreases corn yields by 0.67 percent. Note that this negative temperature effect is larger than 0.55 percent in Table 1, suggesting that irrigation technology mitigates the negative temperature effects on corn yields. One percent increase in the share of irrigated corn acreage mitigates the negative hot temperature effect by 0.0066 percent. At the extreme case where corn production is entirely irrigated (i.e., the share of irrigated corn acreage is 100 percent), corn yields are almost fully resilient against extremely hot temperatures above 28°C.[11]

Our study further submits that farmer's adaptation is facilitated by farmer's adaptation ability. We test whether farmer's aging lowers farmer's adaptation capability and subsequently affects the sensitivity of crop yields to extreme temperatures. This potential decline may stem from diminishing cognitive and physical skills and/or a lack of incentives for investment in adaptation measures. The graphical results of the estimation in Figure 8 show that age marginally mitigates the negative temperature effects at a diminishing rate.[12] Farmers at the age of 35–64 are most capable of reducing the negative hot temperature effects, while such capability diminishes as they get younger/older.[13] The point estimates for hot temperature effects are provided in Appendix Table A5. Specifically, at the age range of 35–64, the negative impact of hot temperatures is estimated at 0.46 percent, approximately 1.2 times lower than the estimate of 0.55 percent reported in Table 1.

To explore the heterogeneous age effect under different climate risks, we segregate estimation results in irrigated (high irrigated and low irrigated) and rainfed counties. We assign counties with no irrigation use in 2002–2017 as rainfed counties, and irrigated (high irrigated: average irrigation uses between 0–30 percent; low irrigated: average irrigation uses above 30 percent, which is about 75 percentiles) counties otherwise.

[11] Given corn's high sensitivity to hot temperatures and minimal sensitivity to colder temperatures in the US, our analysis in this section predominantly concentrates on the impacts of hot temperatures. Results regarding the impacts of cold temperatures are accessible upon request.

[12] We also find the inverted U–shape relationship between age and corn yields, which is consistent with Tauer (1984).

[13] The foundational age bracket considered in this study ranges 35–64 years old.

Table 2. Irrigation effects on the corn yield response function to hot temperatures

	(1)	(2)	(3)	(4)
GDD above threshold	-0.0063***	-0.0067***	-0.0060***	-0.0060***
	(0.0007)	(0.0009)	(0.0005)	(0.0006)
GDD above threshold	0.0064***	0.0066***	0.0063***	0.0062***
× irrigation	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Irrigation	1.8074***	2.0638***	1.9771***	1.6164***
	(0.3573)	(0.4891)	(0.4427)	(0.4705)
Observations	16,985	16,985	16,985	16,985
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	Yes	Yes	Yes	Yes
Adjusted R^2	0.7478	0.8314	0.7328	0.7178

Notes: See *Notes* in Table 1. Irrigation unit: 0–1 (e.g., 0.1 means 10 percent).

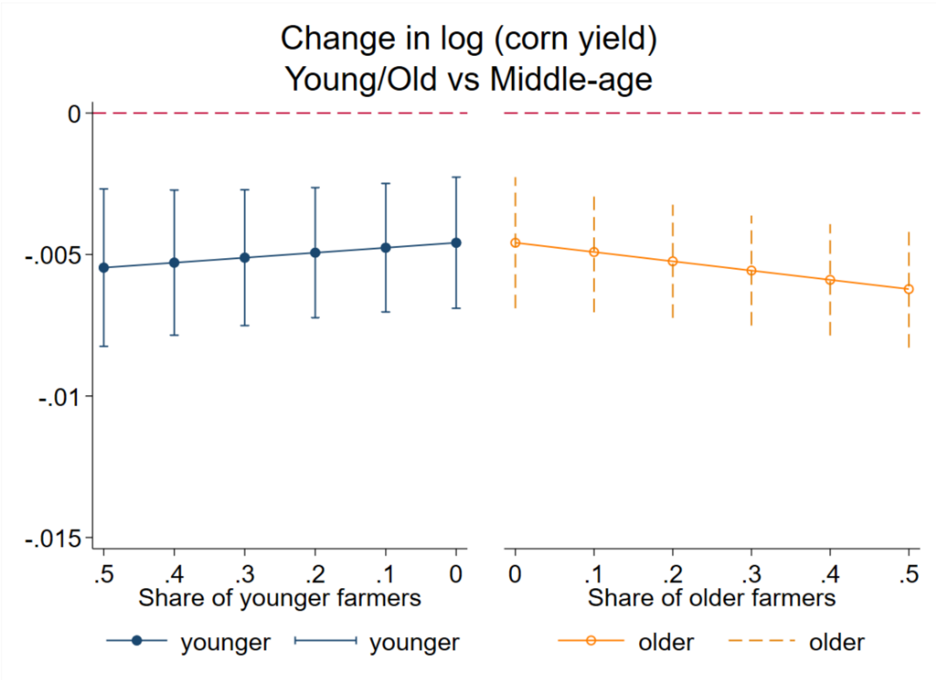

Figure 8. Age effects on the corn yield response function to hot temperatures

Notes: Parameter estimates in Appendix Table A5 are transformed into the marginal change in log corn yields concerning an increase in younger/older farmers relative to middle–aged farmers. We set the value of older farmers to 0 on the left–hand side and the value of younger farmers to 0 on the right–hand side. The midpoint represents when all farmers are middle–aged. The dots represent the impact of age on the yield–temperature response function, while lines depict the 95 percent confidence intervals. Age unit: 0–1 (e.g., 0.1 means 10 percent).

In irrigated areas, exposure to climate risk is relatively low as argued above with Table 2. Figure 9 presents evidence to suggest that the age effect in irrigated regions is less pronounced when compared to rainfed regions. The point estimates for hot temperature effects are provided in Appendix Table A6. Our findings indicate that in rainfed areas, for every one percent reduction in the age of farmers below 35/above 65 years old, there is a corresponding reduction of 0.0048/0.0025 percent in the adverse impact of hot temperature on crop yield, as compared to farmers aged between 35–64 years old. Conversely, the corresponding percentage decrease in irrigated areas is minimal, closer to 0. This suggests that age–related adaptation capability plays a critical role in introducing adaptation measures in areas at high risk of exposure to extreme temperatures.

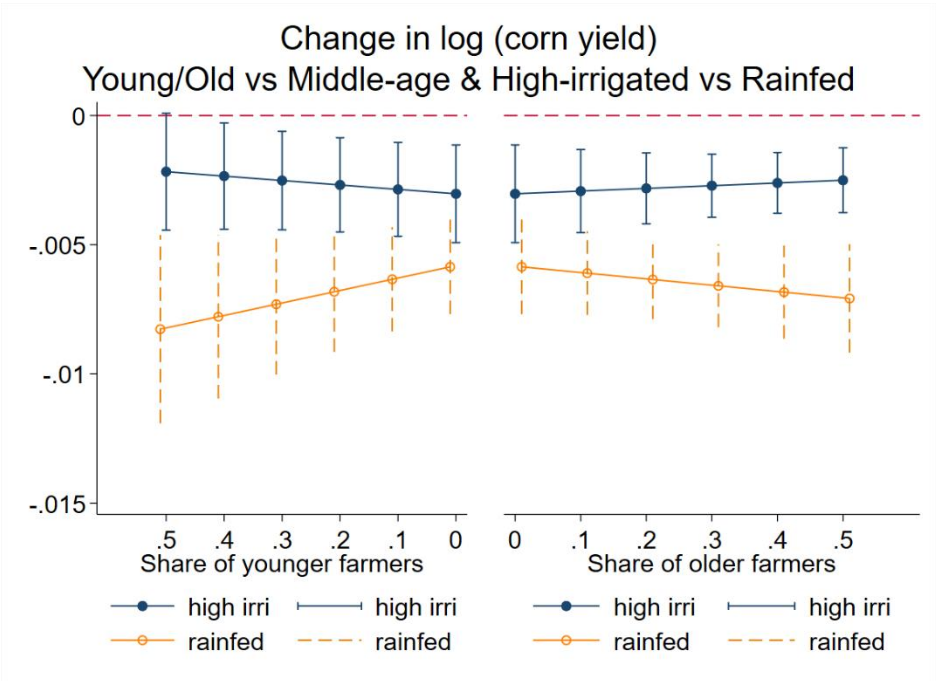

Figure 9. Age effects on the corn yield response function to hot temperatures: irrigated vs. rainfed counties

Notes: See *Notes* in Figure 8. In the visualization, we exclusively present the results for high irrigated and rainfed counties. The age impact on the sensitivity of crop yield to temperatures in low irrigated counties falls between that of high irrigated and rainfed counties. Table point estimates are provided in Appendix Table A6, and graphical results for low irrigated counties are available upon request. Age unit: 0–1 (e.g., 0.1 means 10 percent).

IV. Conclusion

This study investigates how farmer's age and irrigation use affect the yield–temperature relationship by using the panel and GDD methods. Our findings indicate that both age and irrigation practices are crucial factors that alleviate the adverse effects of extreme temperatures on crop yields. Increased irrigation usage leads to a reduction in yield losses due to extreme temperature events. Furthermore, our analysis reveals that age nonlinearly influences farmer's adaptation capability to reduce the negative temperature effect: Capability generally increases and then decreases with age (inverted U–shaped age effects). Notably, the impact of age is less pronounced in irrigated areas, where exposure to climate risk is relatively low. This suggests that human capital plays a critical role in introducing adaptation measures in areas at high risk of exposure to extreme temperatures.

These findings have significant policy implications for avoiding further declines in crop yields under climate change scenarios. Adopting irrigation technology is effective in reducing the negative temperature effects on crop yields. In addition, to enhance the adaptation capability of crop production in the absence of irrigation technology, sufficient investment in human capital is essential. Facilitating the transfer of knowledge and experience from older to younger farmers is an important aspect of this endeavor. Additionally, effective communication of climate change risks is crucial for both inexperienced and older farmers, with extension services playing a pivotal role in this regard.

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Appendix

Table A1. Summary statistics

	Obs.	Mean	SD	Min	Max
Corn yield (bushels/acre)	16,985	137.02	36.72	10.36	246.67
GDD below threshold (D)	16,985	3603.67	470.56	2221.76	4839.20
GDD above threshold (D)	16,985	79.52	74.74	0.005	569.12
Precip below threshold (cm)	16,985	-1.68	4.34	-43.03	0.00
Precip above threshold (cm)	16,985	15.21	14.82	0.00	93.05
Age below 35 (0–1)	16,985	0.10	0.05	0.00	0.70
Age 35–64 (0–1)	16,985	0.68	0.08	0.20	1.00
Age above 65 (0–1)	16,985	0.22	0.08	0.00	0.80
Irrigated corn land (0–1)	16,985	0.13	0.24	0.00	1.00
Corn farm size (acres/ farm)	16,985	217.87	157.44	2.82	1559.70

Notes: Only Apr. to Sep. data is used for weather variables. D: degree days. 0–1: 0–100 percent (e.g., 0.1 means 10 percent).

Table A2. Results of the nonlinear temperature effects on corn yields using temperature and precipitation variables only

	(1)	(2)	(3)	(4)
GDD below threshold	0.0002	0.0001	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDD above threshold	-0.0046***	-0.0055***	-0.0047***	-0.0046***
	(0.0006)	(0.0009)	(0.0005)	(0.0005)
Observations	16,985	16,985	16,985	16,985
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	No	No	No	No
Adjusted R^2	0.7112	0.8105	0.7010	0.6816

Notes: See *Notes* in Table 1.

Table A3. Results of the nonlinear temperature effects on corn yields using all counties

	(1)	(2)	(3)	(4)
GDD below threshold	0.0002*	0.0001	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDD above threshold	-0.0048***	-0.0054***	-0.0049***	-0.0049***
	(0.0006)	(0.0009)	(0.0005)	(0.0006)
Observations	22,804	22,804	22,804	22,804
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	No	No	No	No
Adjusted R^2	0.7231	0.8184	0.7123	0.6880

Notes: See *Notes* in Table 1.

Table A4. Parameter estimates of the corn yield response functions to temperatures in irrigated vs. rainfed counties

	(1)	(2)	(3)	(4)
High irrigated counties				
GDD below threshold	-0.0001	-0.0002*	0.00002	0.00002
	(0.0001)	(0.0001)	(0.00004)	(0.0001)
GDD above threshold	-0.0019***	-0.0027***	-0.0019***	-0.0019***
	(0.0004)	(0.0006)	(0.0003)	(0.0004)
Low irrigated counties				
GDD below threshold	0.0003**	0.0001	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDD above threshold	-0.0060***	-0.0063***	-0.0058***	-0.0058***
	(0.0007)	(0.0008)	(0.0005)	(0.0005)
Rainfed counties				
GDD below threshold	0.0002	0.0002	0.0004***	0.0003***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
GDD above threshold	-0.0057***	-0.0069***	-0.0057***	-0.0054***
	(0.0009)	(0.0009)	(0.0008)	(0.0009)
Observations	16,985	16,985	16,985	16,985
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	Yes	Yes	Yes	Yes
Adjusted R^2	0.7450	0.8714	0.7621	0.7635

Notes: See *Notes* in Table 1. We assign counties with no irrigation use in 2002–2017 as rainfed counties, and irrigated (high irrigated: average irrigation uses between 0–30 percent; low irrigated: average irrigation uses above 30 percent, which is about 75 percentiles) counties otherwise.

Table A5. Age effects on the corn yield response function to temperatures

	(1)	(2)	(3)	(4)
GDD above threshold	-0.0037***	-0.0046***	-0.0039***	-0.0041***
	(0.0011)	(0.0011)	(0.0010)	(0.0014)
GDD above threshold	-0.0002	-0.0018	-0.0001	0.0010
× below 35	(0.0027)	(0.0020)	(0.0027)	(0.0037)
GDD above threshold	-0.0039	-0.0033	-0.0033	-0.0024
× above 65	(0.0041)	(0.0019)	(0.0038)	(0.0053)
Observations	16,985	16,985	16,985	16,985
Fixed effects	Cty, Yr	Cty, State-Yr	Cty, State-tr	Cty, Cty-tr
Control var.	Yes	Yes	Yes	Yes
Adjusted R^2	0.7142	0.8120	0.7036	0.6857

Notes: See *Notes* in Table 1. Age (below 35 and above 65) unit: 0–1 (e.g., 0.1 means 10 percent).

Table A6. Age effects on the corn yield response function to temperatures: irrigated vs rainfed counties

	(1) High irrigated counties	(2) Low irrigated counties	(3) Rainfed counties
GDD above threshold	-0.0030***	-0.0068***	-0.0059***
	(0.0009)	(0.0012)	(0.0009)
GDD above threshold	0.0017	-0.0002	-0.0048*
× below 35	(0.0019)	(0.0023)	(0.0027)
GDD above threshold	0.0011	0.0022	-0.0024
× above 65	(0.0019)	(0.0024)	(0.0024)
Observations	16,985		
Fixed effects	Cty, State-Yr		
Control var.	Yes		
Adjusted R^2	0.8296		

Notes: See *Notes* in Table 1. Age (below 35 and above 65) unit: 0–1 (e.g., 0.1 means 10 percent). We assign counties with no irrigation use in 2002–2017 as rainfed counties, and irrigated (high irrigated: average irrigation uses between 0–30 percent; low irrigated: average irrigation uses above 30 percent, which is about 75 percentiles) counties otherwise.