Lower but less severe: The cropland rental price threshold of exposure to heat

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Abstract

Irrigated agriculture in snowpack-dependent surface water systems is characterized by a diverse high value crop mix and a dependence on water supplies rather than precipitation. As a result, producer profits in these systems may be less affected by exposure to high temperatures than crop yields or profits in nonirrigated production systems. We estimate season-total exposure time to each temperature and use penalized regression to detect a threshold effect in the rental prices of irrigated and nonirrigated cropland. Rental prices reflect expectations about future profits given climate conditions, are reported separately for irrigated and nonirrigated cropland, and are less affected by nonfarm factors than farmland values. Conditional on water supply, we find little evidence for a sharp decline in per acre rental price at higher temperatures, though benefits of warmer temperatures decline starting at 25°C for irrigated acres and 20°C for nonirrigated acres. Our results suggest that Ricardian estimates based on the agronomic measure of degree days from 8-32°C and particularly degree days above 34°C may be misleading. While the marginal impact of an additional degree of temperature is smaller, the decline starts earlier and more cropland is affected.

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Introduction

Exposure to high temperatures can result in lower yields (Schlenker and Roberts 2009). Yet producer profits may be less affected by heat exposure since they can choose a crop mix to maximize profits given climate conditions. In regions characterized by large scale production of a few major crops the choice of crops is small and may not provide substantive flexibility to mitigate the harmful effect of high temperatures (Burke and Emerick 2016). But in snowpack-dependent irrigation systems characterized by a high value diverse crop mix such as the coastal and inland western United States, a more diverse viable crop mix may reduce the negative effects of high temperature exposure. At the same time, snowpack in the western U.S. is expected to decline by at least 10 percent by 2050 (Barnett et al. 2005), shifting both the timing and duration of spring runoff and affecting water supplies[4].

In this paper we use penalized regression, splines, and linear models to conduct a threshold analysis of exposure time to each degree of temperature (Schlenker and Roberts 2009) to examine the relationship between high temperatures, agricultural production, and water use in the coastal and inland western United States[5], a region in which irrigated farms produce \$61 billion[6], 15.7 percent of the total value of all U.S. agriculture (USDA-NASS 2019). We focus on the per acre price for cash[7] rental of irrigated and nonirrigated cropland (rental price), which reflects discounted future profits and is less affected by nonfarm factors (Ortiz-Bobea 2019). Since the rental prices of irrigated and nonirrigated cropland are reported separately, we can precisely distinguish between the effect of exposure to high temperatures on the two production systems in a way that is not possible with land values. We use the threshold points to estimate the effect of exposure to high temperatures based on the agronomic concept of degree days (Schlenker et al. 2006) in which the effect of exposure to temperature scales linearly within a temperature range, often from 8-32°C, with high temperatures occurring above 34°C. To our knowledge, this is the first paper to use

[4] Groundwater irrigation draws primarily from aquifers, which recharge from precipitation that falls throughout the year. While aquifer recharge is affected by surface water flows and thus to some extent by snowpack, it is less directly related. We focus on surface water.

[5] Consisting of Arizona, California, Oregon, Washington, and Idaho.

[6] Total sales for irrigated farms with no nonirrigated production are slightly lower, at \$48.2 billion.

[7] Cropland can be rented on a cash basis, but also rented on a crop share basis, earning a portion of the crop yield.

cropland rental prices to estimate a threshold for the effect of exposure to temperature on the value of agricultural production, and the first to focus on snowpack-driven surface water dependent irrigated production systems.

We use per acre rental prices because they likely better reflect the value of agricultural production than land values (Ortiz-Bobea 2019). Many Ricardian estimates of the effect of climate on agricultural production are based on farmland values (Mendelsohn et al. (1994); Mendelsohn and Dinar (2003); Schlenker et al. (2005); Schlenker et al. (2006); Schlenker et al. (2007); among others), recognizing that land values incorporate climate effects because they reflect the discounted value of future production conditional on climate. However, land values may incorporate the discounted expected future value of conversion from farmland to residential or commercial use, biasing values upward where future development is more prominent (Ortiz-Bobea 2019). The market for farmland is also notoriously thin, characterized by few transactions and long holding times (Bigelow et al. 2016). Market values as measured by the Census of Agriculture are self-assessed rather than from actual transactions, and lead to differences in estimates of marginal effects from values drawn from transactions (Bigelow et al. 2020). Finally, neither farmland values nor the rental value of land and buildings are reported separately for irrigated and nonirrigated land, in part because about 40% of cropland in the coastal and inland western United States is a mix of both irrigated and nonirrigated land (USDA-NASS 2019). Schlenker et al. (2005) use the share of irrigated acres to designate counties as irrigated or nonirrigated, but land values in these counties still reflect a combination of both irrigated and nonirrigated production except where there is little or no nonirrigated production.

Rental prices may not accurately reflect the value of agriculture if rented land is not representative of agricultural land in the county, as could be if highly productive land is less likely to be rented or if perennial crops are less likely to be planted on rented land. While we are not aware of data on the representativeness of rented land in a given county, rented cropland is less likely to be biased because it comprises a significant portion of total cropland. According to the 2014 Tenure, Ownership, and Transition of Agricultural Land (TOTAL) survey, more than 33 million acres of cropland were rented in 2014. This is more than 50 percent of total cropland acres recorded in the 2012 Census of Agriculture. Of the more than 80 million acres of rented farmland (which includes pasture and agricultural uses other than cropland), more than 55 million were rented on a fixed cash basis. While the TOTAL survey did not ask about irrigated or nonirrigated rented land or about whether land rented on a fixed cash basis was cropland, it is clear that rented cropland is a significant portion of total cropland, and that most rented land is rented on a fixed cash basis. Annual leases account for 32 million acres of rented farmland, while 37 million acres are leased for at least four years. On average farmland owners have rented to the same tenant for 10 years.

The use of cash rental prices or other Ricardian outcomes allows us to incorporate adaptation from crop switching or other production changes, but also introduces an interaction between exposure to high temperature in the summer and growing season length. A county with higher summer temperatures has a longer growing season, and those benefits may offset any damage from extreme temperatures. For nonirrigated agriculture in the region east of the 100°C meridian, where many studies focus (Schlenker et al. 2005, 2006; Deschênes and Greenstone 2007; Burke and Emerick 2016), this interaction may not be much of a factor if there is relatively little variation in the growing season (typically defined as April - September), although climate outside of that range may still be important (Massetti et al. 2016). However, in snowpack-dependent surface water systems the growing season can vary substantially. For example, irrigated corn in the southern California and Arizona desert may be planted in January for harvest in May and again in August for harvest in November. In slightly cooler but still warm regions like California's Central Valley, planting may happen as early as February for a July or August harvest. In contrast, irrigated corn isn't typically planted until April in the Washington State's Yakima County. We include climate measures outside of the growing season and consider a number of season specifications to capture the effect of longer growing seasons while balancing the severe multicollinearity introduced by including variables from multiple seasons.

In the following sections we describe our data before then detailing our threshold estimation procedure. We consider a threshold under a number of temperature transformations and growing season definitions and discuss multicollinearity and difficulties with seasonal specifications. In the results section we present our threshold estimates for irrigated and nonirrigated corn yields before moving to cropland rental prices. We also consider land values as a robustness check. Finally, we show the results of a spatial error model in which temperature exposure is measured as degree days within our threshold levels and compare that to results for the common 8-32°C thresdhold. We find that exposure to temperatures above 25°C for irrigated cropland and 20°C for nonirrigated cropland are decreasingly positive. Our results suggest that the typical degree day range may be misspecified when applied to Ricardian estimates.

Data

We construct a dataset consisting of climate, soil, water use, agricultural, and demographic information for all counties with an irrigated cropland-weighted centroid west of the 100° meridian, though our focus is on snowpack-fed irrigation counties in Arizona, California, Oregon, Washington, and Idaho. Our constructed variables closely follow those used in previous Ricardian estimates, including a number of soil and demographic variables. We also follow the literature in limiting our sample to 'nonurban' counties, those with a population density of less than 400 people per square mile. When considering irrigated cropland rental prices, we additionally exclude counties with no surface water withdrawals.

Cash rents and other Ricardian outcomes

Cash rental prices irrigated and nonirrigated cropland are from the USDA-NASS Cash Rents Survey, reported at the county level for most years since 2008 except for 2015 and 2018[8]. The Cash Rents Survey targets all farms and ranches that have historically rented farmland and have $1,000 or more in agricultural sales, asking respondents to report acres and rent paid per acre (or total rent) for irrigated, nonirrigated, and permanent pasture land for all counties with at least 20,000 acres of cropland and pasture. Land rented for free, on a non-cash basis or that includes buildings is not included. The Cash Rents Survey is conducted from the end of February to the beginning of July, before a large part of the year's profits and weather are realized.

Summary statistics for the per acre rental price of irrigated and nonirrigated cropland in

[8]The Cash Rents Survey was completed annual until 2014 and every two years after that as well as in years that the Census of Agriculture is taken.

each year from 2009 are shown in Table 1 for irrigated nonurban counties with some surface water withdrawals. We exclude 2008 because the number of reported counties is small and rental prices differ significantly from later years. The irrigation premium is clear, since irrigated cropland rental prices are more than four times prices for nonirrigated cropland. The variation in rental prices is largely due to cross-sectional differences, although there is a clear time trend that we confirm by regressing rental prices on population, household income and county and year-by-state fixed effects.

Table 1: Summary of Cropland Cash Rents (2012 USD).

	Irrigated Cropland						Nonirrigated Cropland					
Year	n	Min	Median	μ	Max	σ	n	Min	Median	μ	Max	σ
2009	82	42	172	245	1,158	224	47	21	59	67	200	36
2010	93	37	178	233	1,436	230	53	21	55	64	198	34
2011	99	37	168	217	1,396	198	70	14	51	58	195	32
2012	89	33	185	239	1,350	233	61	14	50	59	217	38
2013	86	40	191	256	1,327	235	70	14	43	50	215	36
2014	89	36	214	266	1,544	257	70	9	40	54	222	39
2016	98	26	212	259	1,503	251	63	12	39	47	129	27
2017	102	52	206	256	1,521	257	75	5	42	51	185	37
2019	92	45	207	266	1,869	279	67	16	39	51	210	41
2009-2019	129	35	185	241	1,408	231	111	5	43	48	205	30

Note. Values are on a per-acre basis. Summary statistics are for the 129 counties in the Western Fruitful Rim (AZ, CA, OR, WA, and ID) with a population density less than 400 people per square mile and irrigated cropland cash rent and surface water withdrawals for irrigation reported in at least one year from 2009-2019. No Cash Rent Survey was taken in 2015 and 2018. n is the number of non-missing observations with a full set of covariates.

Previous Ricardian approaches have used agricultural outcomes from the USDA Census of Agriculture, which is produced every five years and reports farm financial information such as farmland value, and the rent paid for land and buildings, as well as irrigated harvested cropland acres. Farmland value has the advantage of having been reported since 1978, making the long differences method employed by Burke and Emerick (2016) possible. We estimate a long differences model using 1997 and 2017 land values, and so present land values for 1997, 2012, and 2017 in table Table 2 for comparison.

Table 2: Summary of Ricardian Outcomes (2012 USD).

Variable	n	Min	Median	μ	Max	σ
				2012		
Irrigated rent	89	33	185	239	1,350	233
Nonirrigated rent	61	14	50	59	217	38
Land & building rent	138	11	103	162	1,122	182
Land value	130	498	2,952	4,284	21,801	3,841
				2017		
Irrigated rent	102	52	206	256	1,521	257
Nonirrigated rent	75	5	42	51	185	37
Land & building rent	146	4	76	150	1,082	174
Land value	132	205	3,064	5,104	40,964	5,461
				2009-2019		
Irrigated rent	129	35	185	241	1,408	231
Nonirrigated rent	129	5	43	48	205	30
Land & building rent	146	4	87	153	993	173
Land value	140	205	2,854	4,563	31,382	4,486

Note. Values are on a per-acre basis. Summary statistics are for counties in AZ, CA, OR, WA, and ID with a population density less than 400 people per square mile and irrigated cropland cash rent and surface water withdrawals for irrigation reported in at least one year from 2009-2019. *Land & building rent* and *Land value* are county total divided by acres of county farmland. 2009-2019 is the average over those years, for which *Land & building rent* and *Land value* are reported in 2012 and 2017, the years of the USDA Census of Agriculture. *n* is the number of non-missing observations.

Climate and available surface water supplies

Our climate measures are derived from gridMET, a dataset of daily meteorological data at a 4-km resolution for which we use data from 1990-2019, which forms our 30-year climate period. gridMET combines the PRISM (PRISM Climate Group) data used in many economic studies with regional measures from the North American Land Data Assimilation System (NLDAS-2) to create a high-resolution dataset that is better suited to the western U.S., where meteorological stations may be a significant distance apart (Abatzoglou 2011).

Following SR, we interpolate between minimum and maximum temperature for each day at each grid point and sum the hours spent at each temperature from -5 to 40°C in each month. Since hours spend outside the bounds are small, we collapse that time to the boundary temperatures such that all hours spent below 0°C are assigned to -1°C and all hours spend above 39°C are assigned to 39°C. We also sum precipitation across each month for each grid point. To create county-level means we take a weighted average where each climate grid point is weighted by the cropland share in the 2012 Cropland Data Layer (National Agricultural Statistics Service 2008-2019), which we first downscale from 30-m to 4-km resolution. The distribution of time spent at each degree for counties with irrigated rental prices is shown in Figure 1.

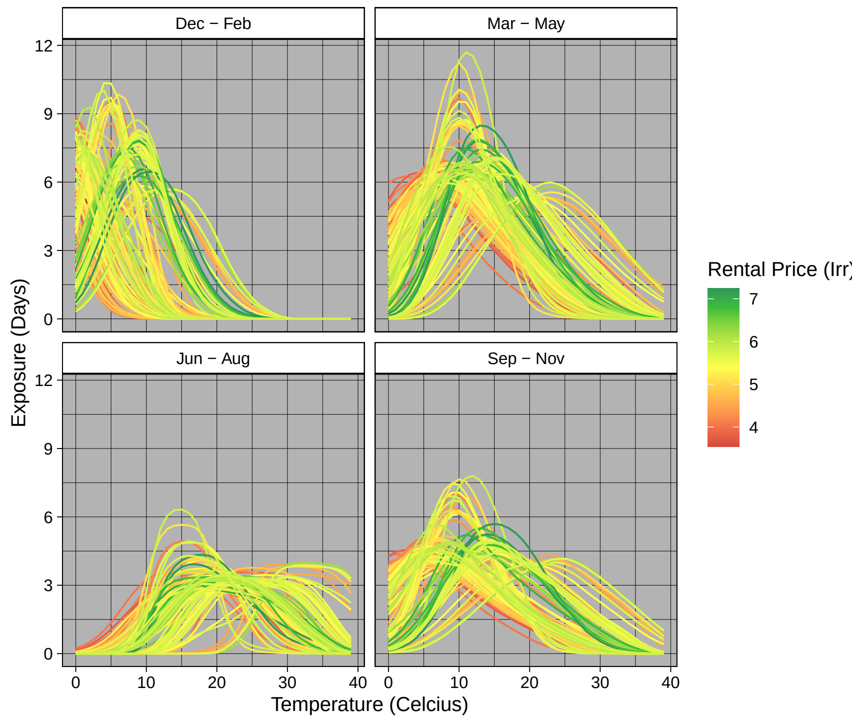

Figure 1: Seasonal exposure to temperature for irrigated counties.

We use exposure to each of the temperature levels in our threshold analysis, but present summary statistics in Table 3 for precipitation and various specifications of degree days.

Other factors

In addition to farm outcomes climate measures, we estimate water use intensity (water use per acre) by dividing each county's total water withdrawals by irrigated acres. We use the average of 2010 and 2015 water withdrawals for agriculture use reported by the US Geological Survey (2015). We use soil and demographic measures to adjust for variation in rental

Table 3: Summary of Climate Variables.

	Irrigated Cropland					Nonirrigated Cropland				
Variable	Min	Median	μ	Max	σ	Min	Median	μ	Max	σ
					June-August					
Degree Days										
8-18°C	507	768	774	920	87	597	757	764	907	79
> 20°C	21	275	357	1,218	251	21	257	301	975	173
8-23°C	594	982	1,015	1,373	171	688	969	988	1,316	151
> 25°C	2	99	158	774	163	2	92	122	587	100
8-32°C	623	1,130	1,210	2,054	310	692	1,102	1,151	1,860	252
> 34°C	0	3	16	183	35	0	2	8	118	15
Precipitation (cm)	0.18	3.59	4.54	13.88	3.36	0.18	4.59	4.91	13.88	3.54
					December-February					
Degree Days										
8-18°C	0	32	102	528	131	0	26	85	457	107
> 20°C	0	0	3	47	8	0	0	1	36	4
8-23°C	0	32	108	602	142	0	26	88	515	112
> 25°C	0	0	0	5	1	0	0	0	4	0
8-32°C	0	32	108	616	144	0	26	88	526	113
> 34°C	0	0	0	0	0	0	0	0	0	0
Precipitation (cm)	3.24	13.65	22.84	96.77	18.91	6.7	18.38	25.97	96.77	19.16

Note. Climate variables are a 30-year averages from 1990-2019.

prices due to these factors. For soil, we use the Gridded Soil Survey Geographic (gSSURGO) Database (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture 2018). gSSURGO is the most detailed soil geographic data available and contains classifications for the suitability of irrigated and non-irrigated agriculture. We average gSSURGO soil observations on land capability class, water permeability, erosion factor, and the percentage of clay, silt, and sand to the county-level using the same weighting scheme we use to create county-level climate measures. Demographic variables are from the U.S. Census and Intercensal estimates and include population and household income. We calculate population density using county land area from the 2017 U.S. Census TIGER maps (2017). Table 4 presents a summary of the water use intensity, demographic, and soil variables.

Table 4: Summary Statistics for Soil, and Demographic Covariates.

	Irrigated Cropland					Nonirrigated Cropland				
Year	Min	Median	μ	Max	σ	Min	Median	μ	Max	σ
Water use (Feet)	0.9	2.9	3.1	13.8	1.6	0.6	2.8	2.7	5.9	1.2
Population density (pop/mi^2)	0.5	31.9	65.9	370.7	85.7	1	34.7	70.1	370.7	90.5
Household income (thousand 2012 $)	30.9	45.3	47.6	74.6	8.3	36.3	45.4	48	74.6	8.1
Fraction clay	0.1	0.2	0.2	0.4	0.1	0.1	0.2	0.2	0.4	0.1
Soil water capacity (cm)	67.2	136.2	148.7	275.1	43	67.2	153.5	158.4	275.1	43.8
Soil permeability	0	0.3	0.3	0.8	0.2	0	0.3	0.3	0.8	0.2
Soil erosion	0.2	0.3	0.3	0.5	0.1	0.2	0.3	0.3	0.5	0.1
Fraction soil in best irr. class	0	0.1	0.2	0.7	0.2	0	0.1	0.1	0.7	0.2
Fraction soil in best nonirr. class	0	0	0.1	0.5	0.1	0	0.1	0.1	0.7	0.1
Latitude (°)	32.3	43.1	42	48.9	4.3	33.6	44	43.1	48.9	3.9
Longitude (°)	-124.2	-119.6	-118.4	-109.1	4	-124.2	-119.8	-119.1	-111.2	3.5

Note. Summary statistics are for the 129 irrigated counties and 111 nonirrigated counties in our sample. *Population* and *Household Income* are the mean from 2009-2019, *Water Use* is the mean of 2010 and 2015. Other variables are time-invariant.

Empirical Approach

In the Ricardian approach an outcome such as land values or per acre rental prices are a function of discounted future profits, which depend on expectations about weather formed from underlying climate, which is defined by climate scientists as the average of weather realizations over a 30-year period. This dependence on climate, renders a typical fixed-effects model unhelpful since we are interested in the time-invariant effects of climate on rental prices. Researchers using a Ricardian approach typically average both outcomes and climate over time and use least squares to estimate the relationship between climate and outcomes (see Mendelsohn and Massetti (2017) for a review). We consider a slightly different approach in which the log rental price is a function of time-invariant characteristics such as climate and soil conditions and time-varying nonfarm factors population density and household income. These nonfarm factors can have significant effects on Ricardian outcomes though they likely play a smaller role for rents than they do for other Ricardian outcomes like land values (Ortiz-Bobea 2019). The model is given by

$$y_{it} = \sum_s \bar{X}'_{is}\beta_s + Z'_{it}\gamma + \theta_i + \varepsilon_{it},$$

where y_{it} is the logged rental price in county i and year t, Z_{it} is a set of annual time-varying covariates that includes household income and a quadratic of population density, and θ_i is a vector of county characteristics that affect agricultural production such as soil. County i's climate in season s is denoted as $\bar{X}_{is}$, which consists of measures of heat exposure and quadratic measures of precipitation.

An alternative approach used by Burke and Emerick (2016) is a long differences, in which averages over a time period separated by some time are estimated in a first difference model. We cannot use a long difference model with rental prices since they begin in 2009, but we estimate a long differences for our irrigated and nonirrigated samples using farmland values. We create our first differences data set by averaging climate for two periods from 1990-1999 and 2010-2019. Farmland values are from 1997 and 2017 and population and income are from 2000 and 2019. We repeat the analysis described below with this model.

For all specifications, we estimate $\hat{\beta}_s$ using a two-stage model based on Hsiao (2014) where in the first stage we regress the log rental price on time-varying factors Z_{it} that include demographic measures as well as county and year-by-state fixed effects. In the second stage, we regress the difference between the county average log rental price and the average estimated value from the first stage, $\tilde{y} = \bar{y}_i - \bar{Z}_i\hat{\gamma}$, on the time-invariant climate and soil characteristics. We also test several alternative approaches. A common method is to average across time and regress using the cross-sectional means, equivalent to assuming no time trend and a balanced panel. However we have neither a balanced panel or data with no time trend. Massetti and Mendelsohn (2011) suggest a pooled model in addition to the Hsiao model, but with true panel data a pooled model underestimates standard errors since the conditional independence assumption does not hold. SR use the average of time-demeaned log yields as their outcome, equivalent to assuming a constant uniform trend shared by all counties. We use all of these approaches but find little difference in estimated coefficients.

Markets for spatially fixed assets like cropland are likely to be spatially correlated (Ortiz-Bobea 2019), so we consider two explicitly spatial approaches. In the first we estimate a spatial error model (SEM) using GMM as proposed by Kelejian and Prucha (1999), allowing for heterogeneity in spatial correlation. This may also remove some bias introduced by omitted factors to the extent that omitted factors are spatially invariant between neighboring counties.

In our second approach, we relax the global independence (conditional on covariates) required for unbiasedness of estimates in our main model and instead assume local independence between spatial neighbors, i.e. conditional on covariates, neighboring counties differ only spatial differences. This allows the use of a spatial first differences (SFD) model described by Druckenmiller and Hsiang (2018). We partition our sample into east-west bands and iterate through each county in each band, pairing it with it's nearest neighbor by crop-weighted center. We then use first differences to estimate the climate-rent relationship using these pairs.

Heat Exposure

A primary goal of this paper is to investigate whether there is a detectable threshold effect in which high temperatures are related to substantially lower rental prices. To do so we follow the approach in SR in which heat exposure is modeled as a transformation of temperature that takes the form

$$H_{ist} = \sum_{h=-1}^{39} g(h+0.5)\phi_{ist}(h)$$

where h is temperature, $g(h)$ is the temperature effect on the outcome per unit of time, and $\phi_{ist}(h)$ is the time of exposure to that temperature in county i during season s and year t. This decomposition allows us to estimate the marginal effect of time exposure to each temperatures. We use several specifications of $g(h)$ to allow for different possible functional forms of the relationship between heat exposure and rental prices. In the least constrained specifications we let $g(h + 0.5)$ be an indicator for exposure to each temperature. More constrained models include specifications of $g(h + 0.5)$ as a natural spline[9] or Chebyshev polynomial, enforcing continuity between effects of exposure to adjacent temperatures. In the most restrictive case we use a continuous piecewise linear model similar to degree days in which exposure effects are linear in temperature up to a threshold at which the slope changes. We iterate over all possible thresholds and choose the model with the lowest AIC.

In the binary specification of heat a reasonable assumption is that there should be some relationship between estimates of effects of exposure time to adjacent temperatures, and assumption that is true of all other specifications. However, exposure to adjacent temperatures is highly correlated, with correlations exceeding 0.95 and remaining above 0.90 for three adjacent degrees or more. To address issues of multicollinearity, we use a ridge regression[10], penalizing the size of estimated coefficients to obtain consistent estimation without adding constraints about adjacent coefficients. We then consider constraints on the relationship between coefficients of adjacent temperature bins using a generalized lasso (Tibshirani and Taylor 2011), which imposes a smoothing penalty on discrete derivatives of the differences between coefficients of adjacent temperature bins. The generalized lasso estimator takes the form

$$\hat{\beta} = \arg\min_{\beta} \frac{1}{2} \sum_{i=1}^{n} (y_i - X_i'\beta)^2 + \lambda ||f(\beta)||_1,$$

where $f(\beta)$ is the the discrete derivative of the difference in adjacent coefficients. By letting $f(\beta)$ be the discrete first, second, or third derivative of estimates of β^{11}, we penalize differences in the levels, linear, or quadratic trend in the coefficients of exposure.

[9] A natural spline is a cubic spline with linear components before the first knot and after the last knot. This prevents the often wild swings at the tails that characterize cubic polynomials.

[10] Ridge regression as a penalty to coefficient size, taking the form $\hat{\beta} = \arg\min_{\beta} \frac{1}{2} \sum_{i=1}^{n} (y_i - X_i'\beta)^2 + \lambda \sum_k \beta^2$.

[11] In the discrete first derivative, $f(\beta) = \beta_{j+1} - \beta_j$ and in the second discrete derivative $f(\beta) = \beta_{j+1} - 2\beta_j + \beta_{j-1}$.

Accounting for Growing Seasons and Multicollinearity

Because our region of interest includes a highly variable growing season, estimates of the effect of exposure to high summer temperatures may be upwardly biased by the benefits of a longer growing season, particularly where winter temperatures are warm enough to double-crop. Many Ricardian estimates will include separate temperature variables for each of four seasons, but this can lead to unstable coefficient estimates that flip signs between season (for example, see Massetti et al. (2016)). We consider several growing specifications designed to capture the benefits of a longer growing season while producing stable estimates. In the first, we consider the April - September season used by Schlenker et al. (2006) and many subsequent papers. We also the four season specification based on meteorological seasons where winter is December - February and summer is June - August. Finally, we consider a specification of growing season length as measured by time spent below 5°C, the temperature that is usually considered the lower bound for crop growth. We present results for the Massetti, Mendelsohn, and Chonabayashi (2016), where we do not include the spring and fall seasons to reduce issues of multicollinearity.

Results

We begin by replicating the method in SR for irrigated and nonirrigated corn yields using heat exposure in days to each three-degree temperature range from 0^{ }Cto39°C and higher over the March - August growing season. We regress log yield deviations from the county mean on heat exposure deviations, using a number of specifications of the temperature transformation function $g(h)$, shown in Figure 2. Regressions include precipitation and precipitation squared as well as quadratic time trends for each state. For the GDD we use a degree day temperature transformation with a lower bound at 8°C and iterate through each successive temperature, choosing the model with the lowest AIC, shown in blue. Degree days for two degrees above that are included as a separate high heat exposure measure. A model with bounds of 8-32°C and $>$ 34°C is labelled "GDD (8-32C)" and shown in green. The two estimates align closely and generally match the other specifications, though the ridge regression estimates are highly unstable. The GDD model estimates that beginning at

34°C, a one degree day increase reduces yields by 1.8 percent. These are closely in line with the results in SR for nonirrigated corn. Irrigated corn yields exhibit a less steep decline of 0.37 percent per additional degree day beginning at 33°C. Since precipitation in the western U.S. does not support nonirrigated corn production, counties for nonirrigated corn yields are drawn from Colorado and New Mexico. In contrast, most irrigated corn in the west is in California.

[FIGURE 2 OMITTED DUE TO SIZE CONSTRAINTS]

The same method using the county average of time-demeaned cropland rents is shown in Figure 3, where the summer season is June - August and temperature variables are also included for the winter December - February season. For the degree day specifications, no high temperature exposure variable is included for the winter season since few counties spend any time above those temperatures. Here the difference between GDD (8-32C) and other specifications is stark for both irrigated and nonirrigated cropland. Where GDD (8-32C) would estimate a sharp decline above 34°C in both cases, other specifications suggest that the beneficial effects of temperature exposure peak at about 20°C and then decline slowly. In both cases, the nonlinear estimates suggest that the decrease in marginal effects slows with an increase in temperature. Other growing season specifications are similar, showing a less steep decline beginning at lower temperatures. In some cases, there is no decline at all.

We use the thresholds in Figure 3 to estimate a spatial error model of the form

$$Y - \rho W Y = X\beta + \varepsilon - \lambda W \varepsilon$$

where W is the spatial weights matrix and ρ and λ are coefficients on the spatial lags. Estimated coefficients are shown in Table 5. For the rental price of irrigated cropland, the effects of December - February exposure to 8-23°C and 8-32°C are similar, estimating that an additional degree day within that range is associated with 0.51% and 0.56% higher rental prices, respectively. But where the 8-32°C model finds no positive relationship between exposure during the summer and a strong negative relationship (-1.7) to exposure above 34°C, our estimated threshold finds a positive relationship between rental prices and exposure to mild 8-23°C temperatures (0.58) and a less steep (-0.27) negative relationship between rental

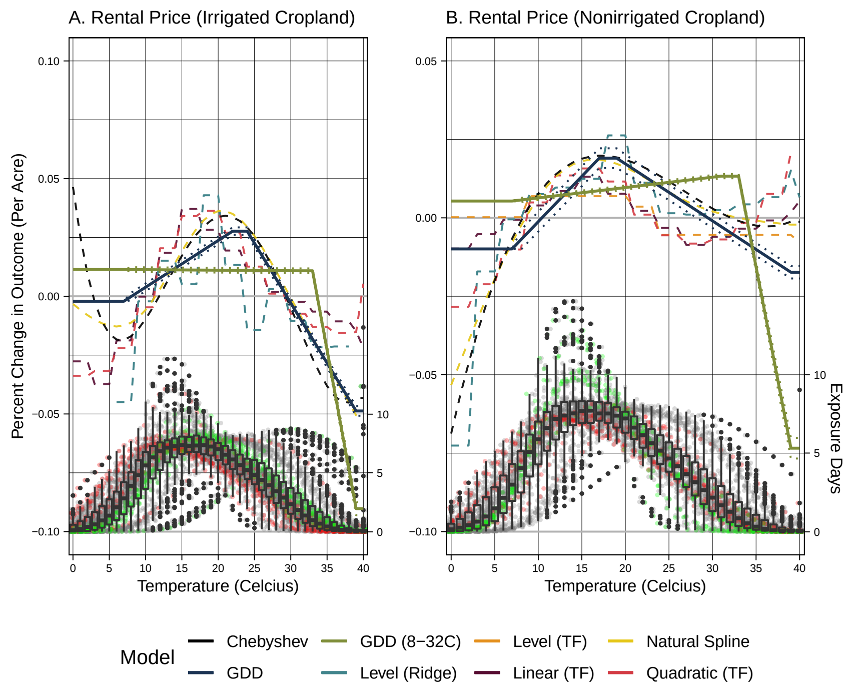

Figure 2: Effects of heat exposure on cropland rental prices.

prices and exposure to temperatures greater than 25°C. For rental prices on nonirrigated cropland the same relationship is true, although the standard GDD model finds no relationship between any exposure to temperature in June - August, whereas the model with our estimated thresholds finds that an additional degree day at mild summer temperatures is positively associated with 0.33% higher rents.

Conclusion

Previous estimates of temperature thresholds have focused on crop yields or used crop-based degree day ranges such as 8-32°C or 10-30°C. However, producer profits and hedonic measures of value should be less sharply affected by exposure to higher temperatures where producers have sufficient degrees of freedom to mitigate negative climate impacts through changes in crop mix, growing season, or production practices. We estimate thresholds for the rental price of irrigated and nonirrigated cropland in a region that contains a diverse high value crop mix and should offer higher degrees of freedom than agricultural production in many other regions. As such, our estimate of temperature threshold are conservative in that more constrained regions have a reduced ability to mitigate negative climate impacts.

We estimate several alternative specifications and models to examine how extreme multicollinearity or omitted variable bias may affect our results. Extreme multicollinearity is a problem when considering specifications of climate that extend beyond a single growing season since variables in different seasons are highly correlated. In our main specification we exclude variables for spring and fall, but other specifications in which we use exposure to temperatures below 5°C in place of winter temperatures yield similar results. Where we include all seasons, variable inflation factors often exceed 20 and estimates become unstable. A second concern is the difficulty of obtaining clear identification with Ricardian outcomes is difficult due to their dependency on climate rather than on annual weather realizations. We obtain similar results with a spatial first difference model, and though the assumption of conditional spatial independence is likely stronger than the conditional temporal independence required of a typical first difference model, a robustness test by varying the direction of pair matches yields consistent estimates. The effect of exposure to high temperatures on nonirrigated rental prices is limited by survivor bias, since in hot and dry counties like many of the hottest counties in our sample there is not enough nonirrigated agriculture to warrant the collection of rental price information. However, in our sample of 110 nonirrigated counties, 23 counties are exposed to more than five days of temperatures above 34°C. This suggests there is likely enough exposure to detect negative marginal effects of exposure to high temperatures, although it does not remove the potential for bias due to unobserved factors.

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Table 5: Regression Results.

	Rental Price (Irrigated)		Rental Price (Nonirrigated)	
	DD 8-23°C, 25+	DD 8-32°C, 34+	DD 8-18°C, 20+	DD 8-32°C, 34+
Winter Low DD	0.51 ***	0.56 ***	0.58 ***	0.71 ***
	(0.14)	(0.11)	(0.14)	(0.14)
Summer Low DD	0.58 *	-0	0.33 *	0.06
	(0.26)	(0.03)	(0.16)	(0.06)
Summer High DD	-0.27 ***	-1.7 ***	-0.2 *	-2.14
	(0.07)	(0.4)	(0.08)	(1.22)
Winter Precip (cm)	-4.01 *	-5.2 **	-7.04 ***	-7.93 ***
	(1.68)	(1.77)	(1.66)	(1.68)
Spring Precip (cm)	-2.26	-3.12	2.39	1.61
	(2.73)	(2.57)	(2.36)	(2.59)
Summer Precip (cm)	-17.67 ***	-24.91 ***	-20.17 **	-20.27 **
	(5.31)	(5.03)	(7.62)	(7.82)
Fall Precip (cm)	9.73 ***	14.51 ***	11.71 ***	14.57 ***
	(2.9)	(2.84)	(3.15)	(3.24)
Winter Precip^2 (cm)	0.13 ***	0.14 ***	0.09 **	0.1 ***
	(0.03)	(0.03)	(0.03)	(0.03)
Spring Precip^2 (cm)	-0.29 **	-0.26 *	-0.18	-0.15
	(0.11)	(0.11)	(0.1)	(0.1)
Summer Precip^2 (cm)	0.67	0.96	1.5 *	1.36
	(0.61)	(0.59)	(0.73)	(0.75)
Fall Precip^2 (cm)	-0.1	-0.16 **	-0.12 *	-0.16 **
	(0.06)	(0.05)	(0.05)	(0.06)
Observations	128	128	110	110

Note. All values are multiplied by 100 for display. Heteroskedastic-robust standard errors are shown in parentheses. Climate variables are thirty-year (1990-2019) averages of cumulative measures over each season, where summer is June-August and winter is December-February. Regressions for irrigated counties include per acre water use. All regressions include soil characteristics and state fixed effects. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.