Historical Evidence of Increased Climatic Resiliency due to Irrigation in the United States

Eric C. Edwards, *North Carolina State University*
eric.edwards@ncsu.edu

Steven M. Smith, *Colorado School of Mines*
ssmith1@mines.edu

December, 2019

Abstract
We consider how technological innovation impacts climate resiliency in the context of agricultural production and irrigation in the United States, where irrigated cropland now accounts for nearly half of production. During the 1940s stored water for irrigation become more widely available: surface water through large dams and associated irrigation works, and groundwater through rural electrification and center-pivot sprinkler technology. In this paper we hold constant overall productivity increases in the arid US west to understand the role irrigation technology has played in mitigating climatic shocks. Characterizing significant drought as county precipitation at least 1.5 standard deviations below normal, we examine relative changes in agricultural production in counties with access to water storage. Prior to 1950, a county having a severe drought saw a 20-30% decrease in the value of crop production. After 1950, counties without increased access to stored water, ground or surface, saw a 24% decrease in crop value, whereas counties with storage experience no loss, on average. The resilience stems largely from areas with groundwater access, where farmers are able to increase irrigated acreage during drier conditions. Our findings suggest that expanded storage mitigates climatic shocks, providing benefits that are additional to a county's average irrigation productivity increase. These patterns are important to understand as we document that even the more humid eastern counties are increasingly investing in irrigation and demonstrate similar abilities to increase irrigated acreage during droughts.

JEL Codes: N52, Q15, Q54, Q55

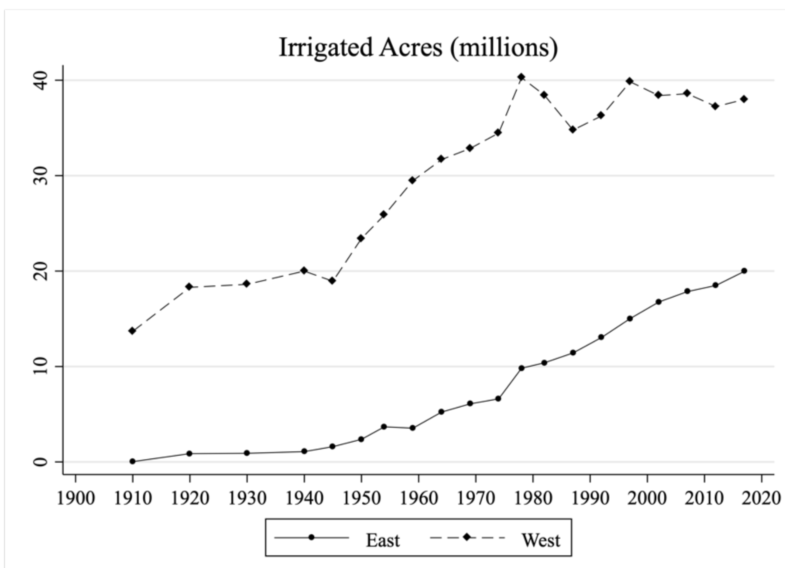
Manuscript prepared for the Allied Social Sciences Association Annual Meeting, San Diego, January 3-5, 2020.

1. Introduction

Extreme weather shocks like heatwaves and droughts are linked to reduced economic output, especially in the context of the developing world and where agricultural output is an important contributor to the overall economy (Dell et al. 2012; Dell et al. 2014). In the United States, the focus of this paper, anthropogenic climate change is expected to increase the frequency of high temperature days and drought (Strzepek et al 2010). The ability of farmers to mitigate the effects of these weather shocks will be crucial to ensuring a secure and reliable food supply. The adoption of irrigation practices may provide resilience—defined here as the capacity of a farm to absorb yearly deviations from mean weather without production losses—by allowing farmers to maintain crop yields through the application of supplemental water obtained through dams and diversion canals or groundwater pumps (Zhang and Lin 2015; Tack et al. 2017; Zaveri and Lobell 2019; Troy et al 2015). However, while there has been considerable discussion in the literature of the impact of weather shocks on agricultural yields, the magnitude of the economic benefits of irrigation are not fully understood. The literature on climate change and its impact on agriculture has largely set aside irrigated areas, which are viewed as institutionally complex and not a reliable counterfactual for non-arid regions experiencing more climatic variability (e.g. Schlenker, Hanemann, and Fisher 2005). We choose to focus on irrigation, however, because it accounts for a significant and disproportionate share of US agriculture production by value – 53 percent of the total crop value in the US in 2017 was generated on irrigated farms while only 29 percent of harvested cropland was irrigated (USDA 2019) – and, despite being viewed as an adaptation for historically arid areas, farms in the humid eastern US have expanded irrigated acres and continue to do so, now accounting for over one-third of the country's total irrigated acreage (see Figure 1).

The history of drought and response in the western United States offers compelling reason to think irrigation plays a key role in climatic resilience. In the 19th and early 20th Centuries, the region saw two prolonged droughts with severe economic impacts that led to significant political and social change. Drought from 1890-1896 led to a dramatic reversal of westward immigration trends and economic depression across the Great Plains. The Dust Bowl, a period of drought and wind erosion that occurred in portions of the Great Plains from 1930-1936 is perhaps the most important human-natural disaster in American history (Hansen and Libecap 2004; Hornbeck 2012). Compared to these events, later droughts, similar in magnitude, appear to have been much less impactful, with droughts in the 1950s and 1970s not leading to the same levels of wind erosion, nor similar levels of economic or social upheaval (Hansen and Libecap 2004). The sudden availability of significant additional stored water across the western US, subsequent to the Dust Bowl, appears a likely explanation for divergent response to drought over time. Beginning with the completion of Hoover Dam in 1936, federal reclamation projects began to store and deliver water across the west. Shortly thereafter, technological innovation allowed for widespread access to stored groundwater for irrigation on the Great Plains (Hornbeck and Keskin 2014; Hornbeck and Keskin 2015) and across the west (Edwards and Smith 2018).

FIGURE 1
IRRIGATED ACRES IN THE US OVER TIME



Notes: Total acres from USDA agricultural census data bifurcated at the 98th Meridian.

Figure 1 shows the effect of this new water storage in the west, with irrigated acreage increasing steadily from 1945 to 1974. This new acreage increased the productivity of land in the western US by allowing more water intensive crops to be grown, increasing the overall level of agricultural output. In addition, irrigation provides resilience to short-term fluctuations in weather (Zhang and Lin 2015; Tack et al. 2017; Zaveri and Lobell 2019). While the combination of increased production and resilience together explain the western expansion of irrigated acres, in the eastern US sufficient precipitation on average suggests irrigation is adopted exclusively to protect against weather shocks. In fact, eastern counties add more irrigated acres between censuses if they experienced at least one "drought" in the interim.[1] As seen in figure 1, eastern irrigated acres have continued to increase since the 1970s, even as the western US has leveled-out, suggesting that investment to provide climatic resilience through irrigation is increasing. Accordingly, we seek to understand how irrigation, and its different sources of water, provide resilience or robustness to variation in weather.

Because plant growth is sensitive to climate, agriculture is likely to be the sector most affected by climate change. Much of the work in this area explores the short- and long-run impacts of temperature shocks on agricultural productivity, taking two approaches. First, by using cross-sectional variation to compare outcomes regressed on temperature or growing-degree days (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005). Second, by using within-area variation to compare outcomes during relative weather shocks including temperature and precipitation (e.g., Deschênes and Greenstone 2007, 2011; Schlenker and Roberts 2009; Dell, Jones, and Olken 2012). The focus of this literature has been on temperature, and increasing the number of very hot days is consistently shown to have a large, negative effect on agricultural yields, (e.g. Feng et al. 2012; Schlenker et al. 2005). Deschenes and Greenstone (2007) find farmers adapt to short-run climate shocks, but Schlenker and Roberts (2009) and Burke and Emerick (2016) find limited evidence of adaptation in the short- and long-run, respectively.

One cause of disagreement could be that the latter two papers exclude from their main specifications counties from the irrigated west. Irrigation has been documented as increasing farm resilience to precipitation shocks. Corn yields in areas with access to the Ogallala Aquifer are higher during drought than those without access to irrigation water, for some periods (Hornbeck and Keskin 2014). Irrigation districts with access to water from large dam projects in a select group of western states also appear less

[1] This is according to regression estimating the change in irrigated acreage between censuses. Results available in Table A1 of the supplemental material.

sensitive to drought (Hansen et al 2011). In irrigated areas, adaptation decisions during drought, in the short- and long-run, respond to the amount and type of water available for irrigation (Hagerty 2019). Appendix results from Schlenker and Roberts (2009) also suggest significantly lower negative yield responses to temperature shocks in the western US, where substantial irrigation takes place.

In this paper, we examine the response of agricultural production to precipitation shocks and the mitigating role of irrigation. Our empirical strategy uses within-county response to precipitation shocks before and after the large surface storage projects and widespread groundwater irrigation that increased access to stored irrigation water across the western US. Using US Agricultural Census data from 1910 onward, we construct long-term measures of irrigation, crop value, and crop failure as well as production measures of key crops. Because access to this additional storage occurred for some areas but not others, we are able to identify the effect on agricultural outcomes based on potential treatment. Our approach allows us to separately identify the effect of irrigation by water source, to our knowledge the first paper to do so.

2. Methods

We construct a panel data set consisting of 2,920 US counties with 20 observations each from 1910 to 2017. These economic data are digitized by Haines et al. (2018) except for the 2017, downloaded directly from the USDA (2019). Our main analysis uses only the subsample from the arid 17 western states, where water scarcity allows us to use the additional availability of stored water for identification. To address the climactic gradient of the Great Plains, we keep only counties west of the 98th meridian, an approximation of the transition from the sub-humid to semi-arid portion of the US. Data from the United States agricultural census is used to look at crop production (combined value of all crops produced), irrigated acreage, and failed crop acreage from 1910-2017, as well as acres planted in wheat, hay, corn and soybeans for the same period. The monetary measures are adjusted to constant 2007 dollars for inflation using a CPI index.

Because our economic data span a significant portion of the 20th century, we adopt 1910 counties as our observations, reweighting data from other years to fit these borders (Minnesota Population Center 2006). For the process to yield accurate aggregations in all cases, the census farming data would need to be uniformly distributed over space. Though this is unlikely on the whole, most instances are of a single county being divided into two counties in which case the aggregation is accurate independent of the spatial distribution of farms and irrigation. Furthermore, county borders are relatively stable from 1910 onward.

In order to explore the role of irrigation adoption and various levels of storage, we first identify counties that irrigate significant amounts of land within the sample. To do so, we identify the top 70 percent of counties in terms of the average irrigation extent observed post 1950, and drop those that develop less. In practice this cutoff is 0.5 percent of total county area. In terms of irrigation of farmland specifically, those excluded averaged 12 percent of farmland irrigated within the county, whereas the sample we analyze averaged 44 percent of farmland irrigated.[2] For each county we calculate the share of access to various water sources: fraction over an aquifer, fraction within 15 miles of a "large" stream, and the fraction having access to both.[3] Edwards and Smith (2018) demonstrate that these define areas more likely to develop wells, if over and aquifer, and receive stored water from Bureau of Reclamation projects, if near a large stream. To create the categorical assignments for counties used in some of the analysis, we took counties in the bottom 25th percentile and assigned them as "small streams" – those which irrigate but do not have access to surface storage or groundwater supplies – assigning the remaining counties the access type that covers the largest share of county. See figure 2 for a visual of the water resources.

We use data from PRISM (2004) to construct county-level measures of precipitation for every census year from 1910 to 2007. Because our focus is on irrigation, we depend on measures of precipitation in order to classify drought. Generally, precipitation and temperatures covary over time, with hotter years producing

---

[2] Others, focused on non-irrigated counties only, have utilized percentages ranging from 5-20 as a cutoff (Schlenker et al. 2005, Deschenes and Greenstone 2007, Kuwuyama et al. 2018) or simply the 100th Meridian (Burke and Emerick 2016).

[3] Large streams identified as those with a Strahler order of 4 or greater. The Strahler ranking spans from 1 to 7.

less rain. We define drought locally by considering relative deviations from a county's mean. Using precipitation data for each county, i, from 1900-2017, we calculate the mean, $\bar{\mu}_i$, and standard deviation, $\bar{\sigma}_i$. Our measure of precipitation shock in year t is then calculated as follows:

$$\hat{y}_{\mathrm{i,t}} = \frac{\bar{\mu}_i - \widehat{\mathrm{precip}}_{i,t}}{\bar{\sigma}_i}$$

Normal years are assigned as within one standard deviation centered at zero, somewhat dry years as falling between 0.5 and 1.5 standard deviations below the mean, and significant drought years anything beyond 1.5 standard deviations. We similarly define wetter years on the other side of the distribution. Figure 3 provides visualizations of the precipitation and temperature data broadly as well as for census years specifically. Notably, while there is annual variation across the sample, within any given year there is also considerable variation of counties experiencing relatively wet or dry years. In addition, while the West is generally drier and cooler than the East, both regions display a negative correlation between temperature and precipitation. Figure 4 shows the spatial distribution of this intra-annual variation for the wettest and driest years in the sample.

To explore the differential effect of increased storage on resilience to precipitation shocks, we regress the outcome variable of interest on the interaction between the realized precipitation shock bin, $\mathrm{Bin}_{\mathrm{it}}^{\mathrm{j}}, j \in (-2,2)$, and a dummy for whether county i receives storage treatment after 1950, $\mathrm{Stor_i}$:

$$\mathrm{Y_{it}} = \sum_{\mathrm{j}=-2}^{2} \alpha^{\mathrm{j}} \cdot \mathrm{Bin}_{\mathrm{it}}^{\mathrm{j}} + \sum_{\mathrm{j}=-2}^{2} \beta^{j} \cdot \mathrm{Stor_i} \times \mathrm{Bin}_{\mathrm{it}}^{\mathrm{j}} + \tau_{\mathrm{t}} + \gamma_{\mathrm{i}} + \mathrm{u_{it}} \qquad (1)$$

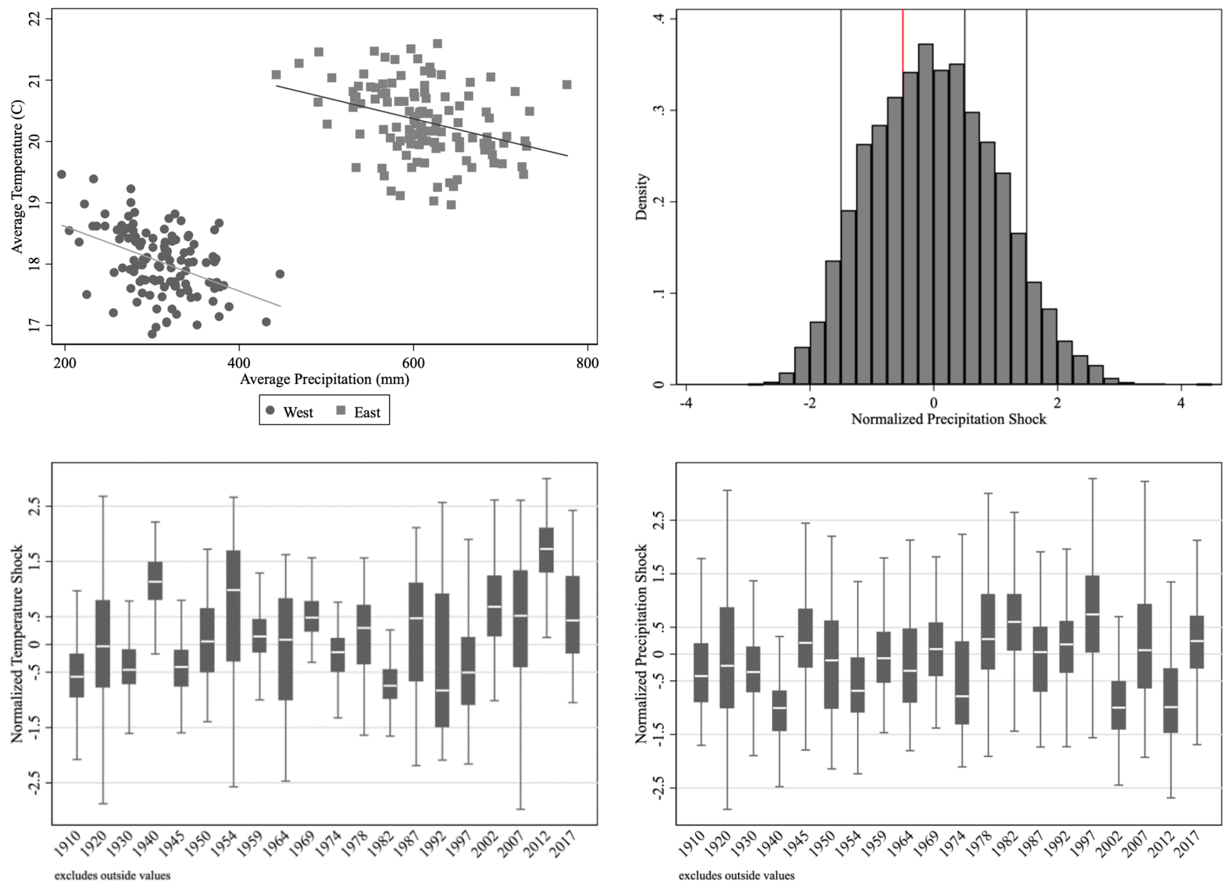
In these regressions we exclude the third bin ($-.5 \leq \widehat{\gamma_{i,t}} \leq .5$) and counties without storage are the baseline. τ_{t} and γ_{i} absorb time and county fixed effects. The key identifying assumption is that conditional on covariates county precipitation shocks are not correlated with outcome variables. The above regression is run separately on pre- and post-1950 observations.

To examine how *k* different types of storage technology differentially affect the response to precipitation shocks, we change the storage variable from binary to categorical, allowing for multiple combinations of storage type and precipitation interactions:

$$Y_{it} = \sum_{j=-2}^{2} \alpha^{j} \cdot Bin_{it}^{j} + \sum_{k} \sum_{j=-2}^{2} \beta^{jk} \cdot Stor_{i}^{k} \times Bin_{it}^{j} + \tau_{t} + \gamma_{i} + u_{it} \qquad (2)$$

We again run these regressions separately on data pre- and post-1950. Here the coefficient β^{jk} shows the effect of storage type k on climate bin j relative to the same county but with no storage in the middle climate bin.[4]

FIGURE 3
VARIATION IN PRECIPITATION AND TEMPERATURE 1900-2017

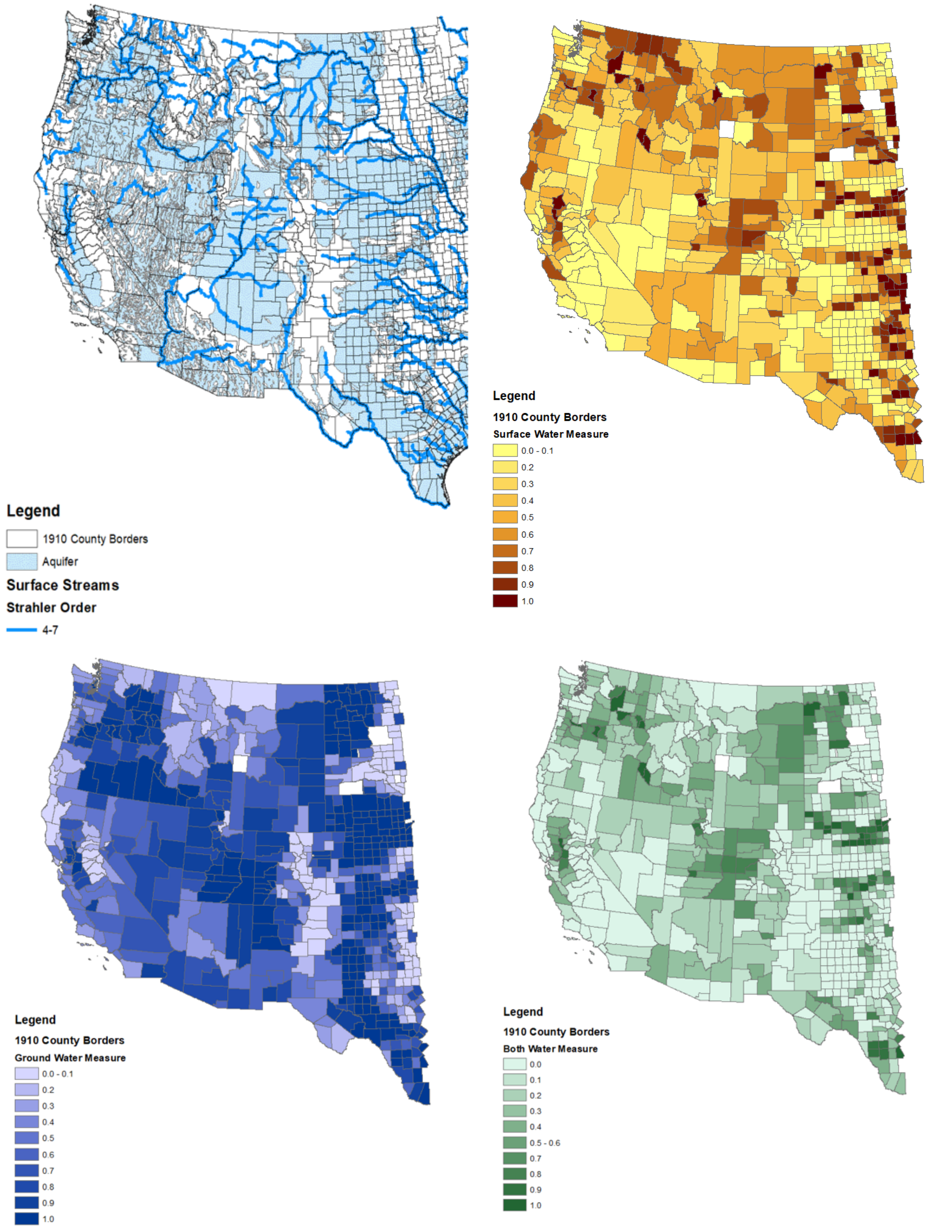


Notes: (top-left) Precipitation and temperature relationships bifurcated at the 98th Meridian. (top-right) normalized western precipitation categorized by bin; Annual averages of temperature (bottom-left) and precipitation (bottom-right) are constructed from county level spatial averages based on the location of the county's centroid. Normalized shocks are the number of standard deviations away from the county's mean precipitation or temperature.
Sources: Authors' rendering of PRISM (2004) data sets and county borders Minnesota Population Center (2006).

---

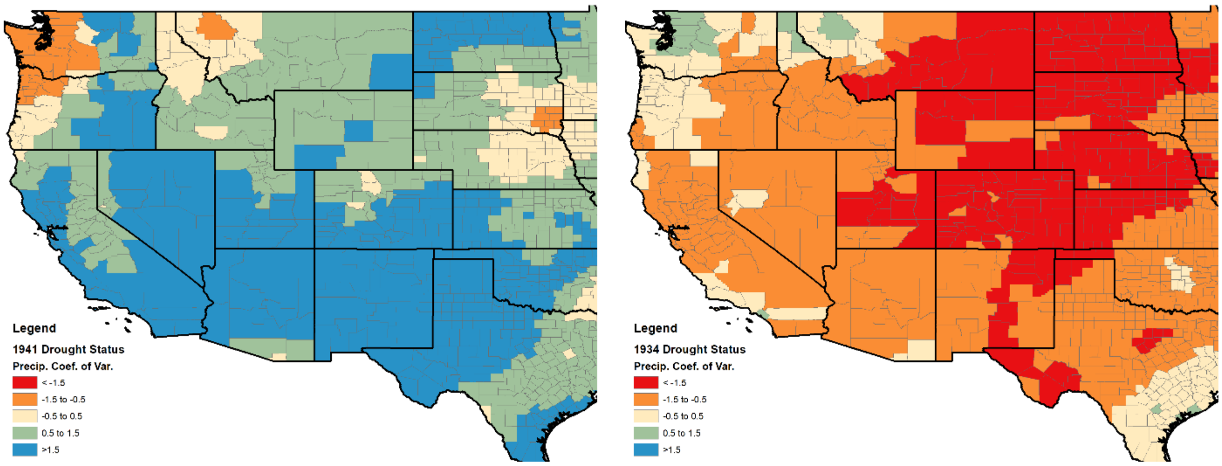
[4] For robustness, we also utilize the continuous measure of irrigation access (fraction of the county overlaying an aquifer, within 15 miles of a large stream, or both).

FIGURE 2
WESTERN COUNTIES AND CONSTRUCTED MEASURES OF WATER ACCESS



Notes: Panel A provides the underlying aquifers and large streams in the Western United States (1910 boundaries)). Panels B–D illustrate the fraction of the county within 15 miles of a large stream, fraction of the county over an aquifer, and the fraction of the county over an aquifer and within 15 miles of a large stream, respectively. For our measure of expanded surface water, we extract stream segment locations from the National Atlas of the United States (National Atlas, 2014). The streams are ranked using Strahler Order, an algorithm-based measure that generally gets larger as tributaries meet. The scale goes from 1 (the smallest streams) up to 7 (largest streams). Because larger streams with more tributaries are better suited for reservoir construction, we build our measure from stream segments of order 4-7. Groundwater is categorized based on the physical presence of an underlying aquifer as located by the US Geological Survey (USGS 2003). As we did with the stream buffer, we calculate the fraction of each county that overlays an aquifer to define the extent of its groundwater access, but do not construct any buffer.
Sources: Authors' rendering of physical data sets: USGS (2003), National Atlas (2014), Minnesota Population Center (2006).

FIGURE 4
COUNTY DROUGHT STATUS BINS FOR HIGH AND LOW PRECIPITATION YEARS



Notes: Map shows the distribution of county bins for the wettest year, 1941, and the driest year, 1934, in the sample. Bins are created using individual county means and standard deviations of precipitation.

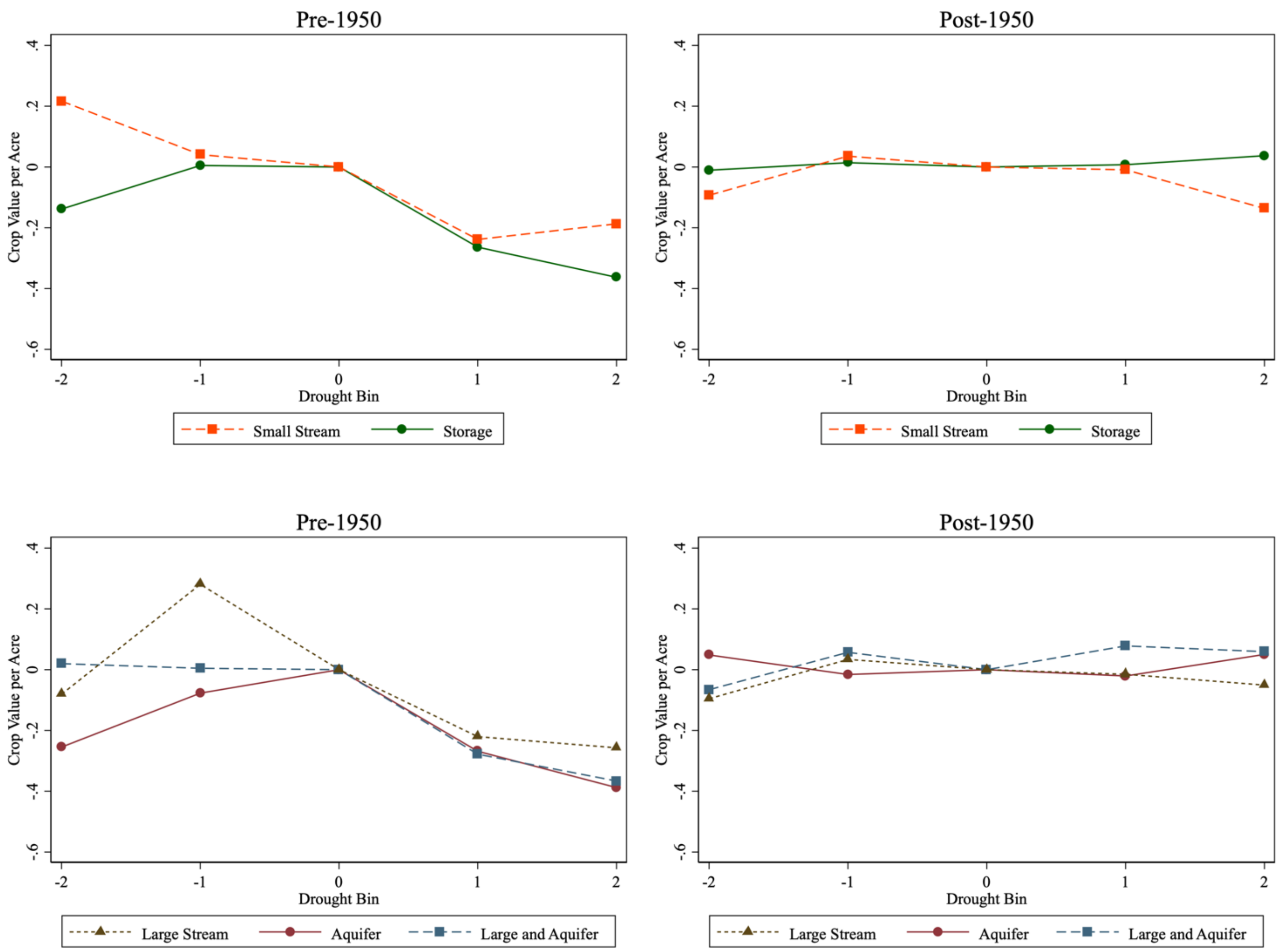
3. Results

Figure 5 plots the estimated coefficients from equation (1) for crop value per acre, both before and after 1950. Regardless of the source of irrigation water, crop production becomes much less responsive to changing precipitation after 1950. In the most extreme shortages (the "+2" bin in the graph), those with access to storage experienced losses of up to 32 percent prior to 1950.[5] In contrast, after 1950, areas with small streams that could not rely on expanded water reserves faced similar losses as before for the highest category of drought, while production became more consistent across the other four precipitation categories. In contrast, counties with storage access experienced large losses in moderate and severe drought years prior to 1950, but the relationship between drought and production virtually disappears after 1950. The bottom panels, omit the *small stream* category, but break up *storage* into its three distinct

[5] Pre-1950 point estimates are provided in the supplemental material, table A2. Post-1950 estimates are in table A3. Table A4 provides estimates using the continuous measure of irrigation access rather than the binary division for after 1950. The estimates for the bottom panels – by irrigation water source – are provided in table A5 (pre-1950) and table A6 (post-1950) with table A7 providing the continuous water type access measure version of the regression post-1950.

types. All storage types see less response to moderate and severe drought than they did before 1950, but those with access to groundwater appear slightly more robust.

FIGURE 5
EFFECT OF IRRIGATION WATER STORAGE ON CROP VALUE BY PRECIPITATION CONDITIONS



Notes: Coefficient estimates of equation 1 (top) and equation 2 (bottom). The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).
Sources: Authors' estimation; see text.

While irrigation technology appears to have improved resilience to weather shocks across sources, this is accomplished through alternative adaption strategies. For instance, when we consider irrigated acres, shown in figure 6, we find that during severe drought, counties with access to storage significantly increase the share of the county irrigated during a severe lack of precipitation.[6] The ability to expand irrigated acreage is driven by areas with groundwater, particularly with access to both.[7] Indeed, aquifer counties exhibit greater variation in the amount they irrigate, swinging up and down by 20 percent (see Figure A3 of the supplemental material). In groundwater areas, these results indicate that farmers are not irrigating all they can in a normal year, providing themselves some margin of response to achieve resilience in drier years.

The reduction in irrigated acres along small streams is in part institutionally driven. Under the prior appropriation doctrine, junior irrigators must curtail their water use when conditions are drier. In contrast, large stream areas, thanks to the stored water, are able to maintain irrigated acreage, but unable to expand irrigation in dry years. This lack of flexibility for surface water is also likely institutionally driven, as often water rights are appurtenant to specific lands and require continued use under the prior appropriation doctrine. Even within larger irrigation districts where the land restriction may be relaxed, the total acreage often remains set, leaving little room to bring additional crop land under irrigation during a drought.

An alternative measure of the effect of drought, failed crops, is shown in Figure 7. Prior to 1950, deviations from normal precipitation, both positive and negative, resulted in increased crop failures. After 1950 variation in failed crops diminished considerably across the board all counties and precipitation conditions. The stability may come from other resilience technology as well as smarter planting decisions.

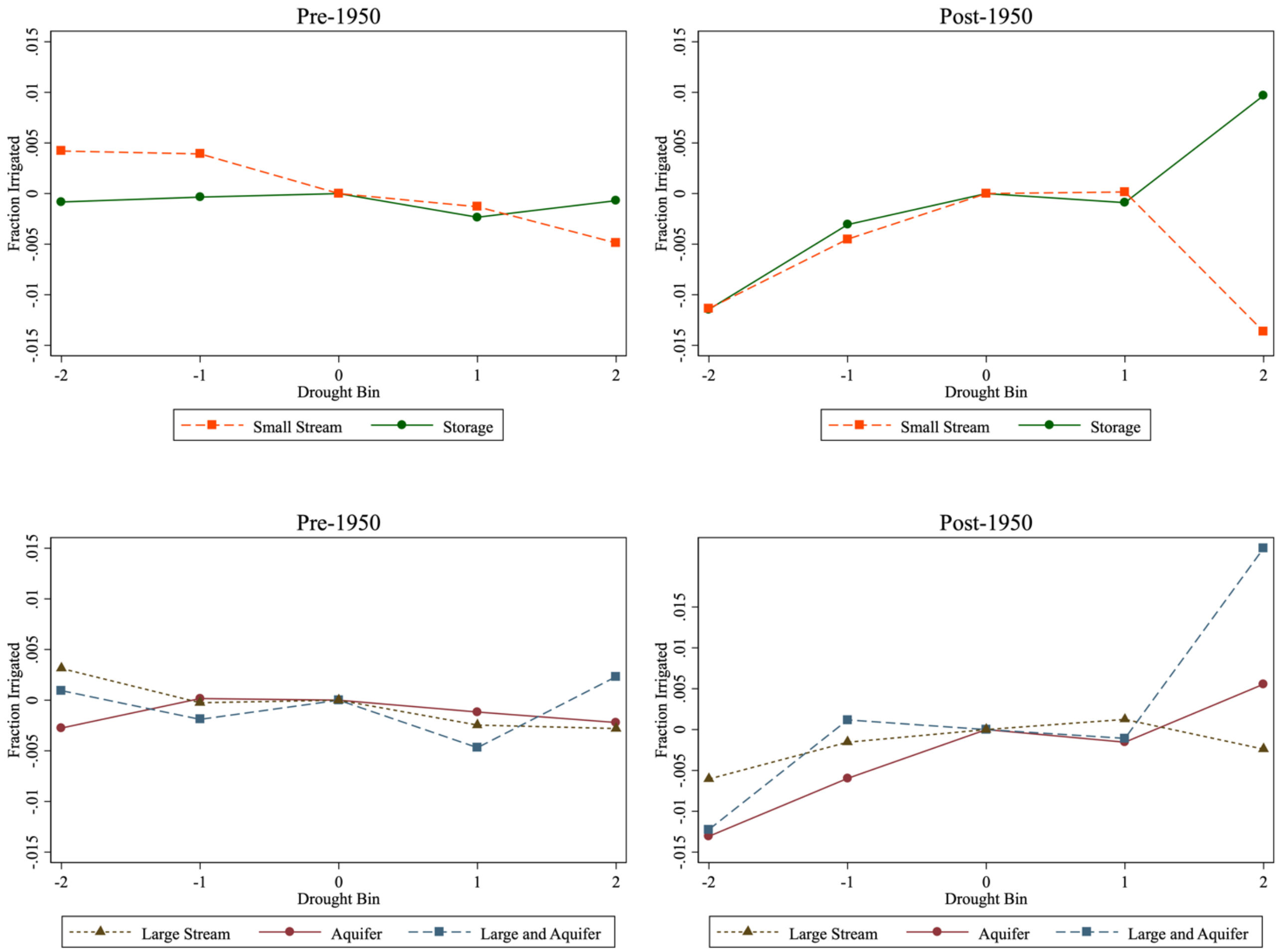
---

[6] Figure A2 in the supplemental material provides the local polynomial of the fraction irrigated data with regard to the continuous measure of standard deviations away from the precipitation norm. Prior to 1950 both small stream and storage counties show declines during drier years, but post the expansion of irrigation in drier years is apparent in the storage counties.

[7] The observed increase is significantly influenced by 2012 observations, the most severe drought in the post-1950 measure by our metrics: 23 percent of our sample is in a drought in 2012 and this accounts for 20 percent of all the “drought” observations after 1950. Still, omitting 2012 from the analysis, provided in supplemental material, figure A1, does not alter the results substantially.

FIGURE 6

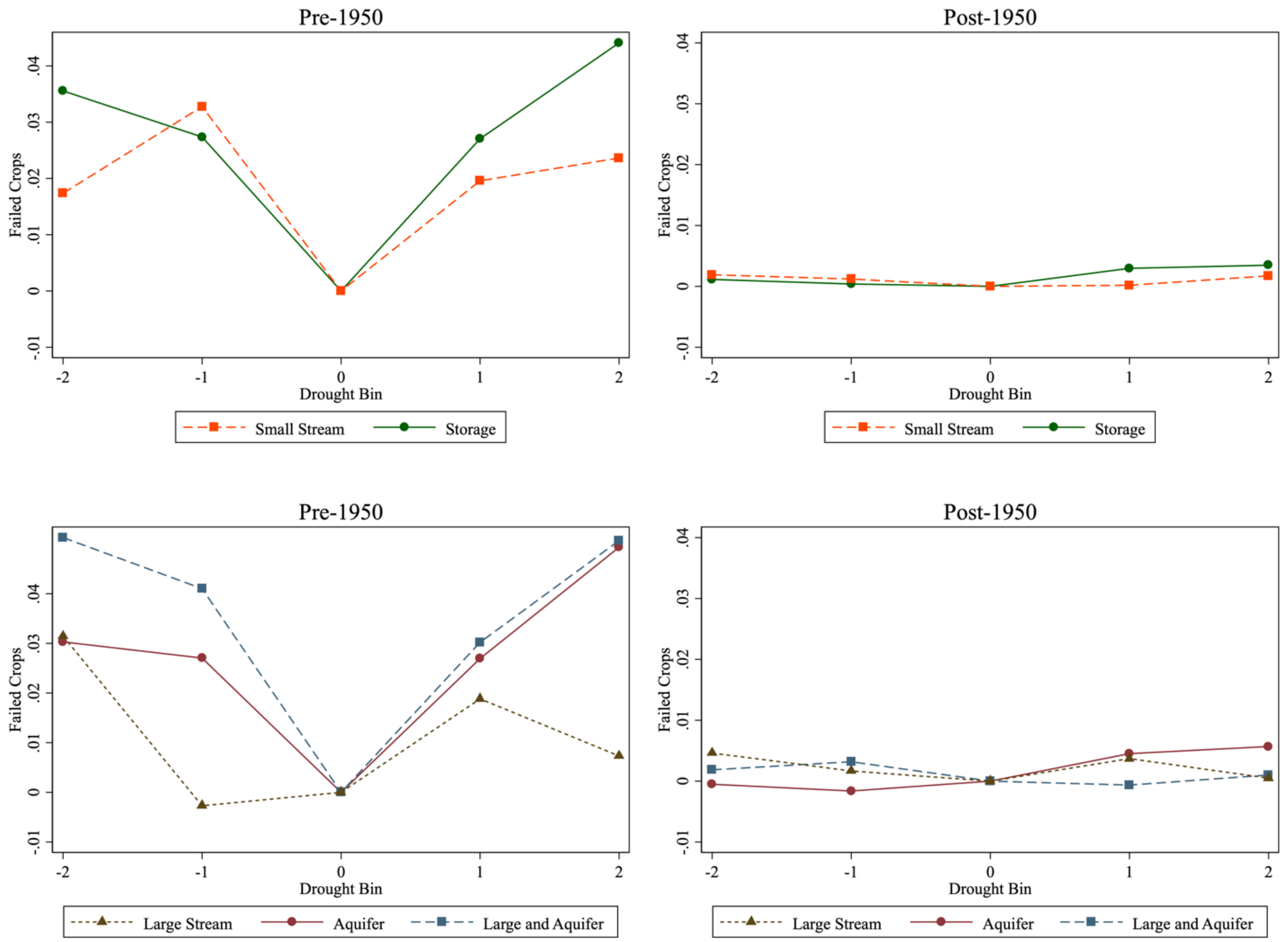
EFFECT OF IRRIGATION WATER STORAGE ON IRRIGATED ACREAGE BY PRECIPITATION CONDITIONS



Notes: Coefficient estimates of equation 1 (top) and equation 2 (bottom). The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).
Sources: Authors' estimation; see text.

FIGURE 7

EFFECT OF IRRIGATION WATER STORAGE ON FAILED CROPS BY PRECIPITATION CONDITIONS

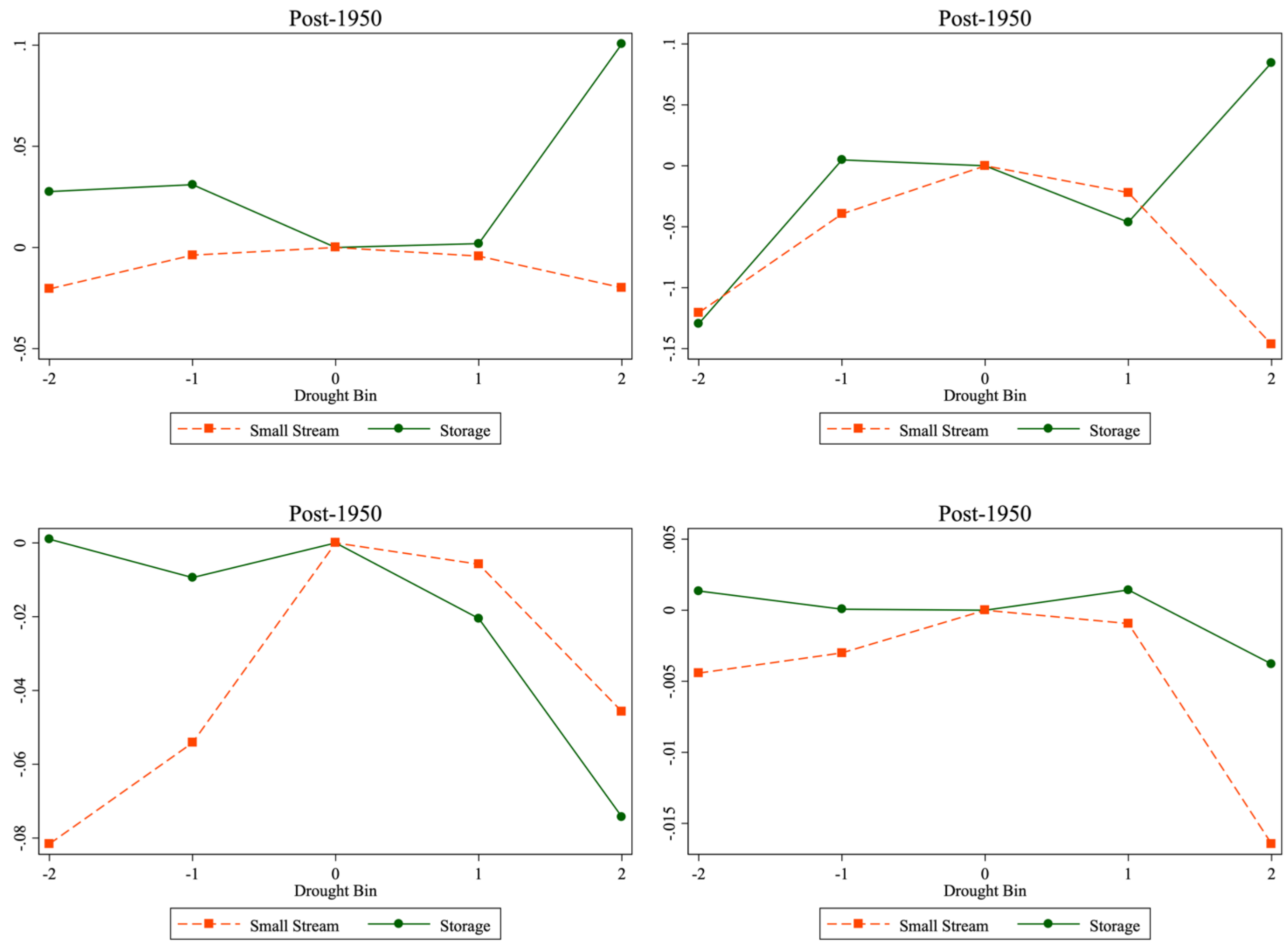


Notes: Coefficient estimates of equation 1 (top) and equation 2 (bottom). The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).
Sources: Authors' estimation; see text.

Finally, we look at how these precipitation shocks impact cropping choices. Here we show just the results for after 1950 in Figure 8. Those with storage maintain higher levels of soy and corn acreage, driven largely by those with access to groundwater. This adaptation is intriguing because it suggests that farmers anticipate the dry conditions and bring more areas with storage, specifically aquifer access (see figure 9), into soybean and corn production. This result is similar to trends seen on the Ogallala (Hornbeck and Keskin 2014, Pfieffer and Lin 2014).

FIGURE 8

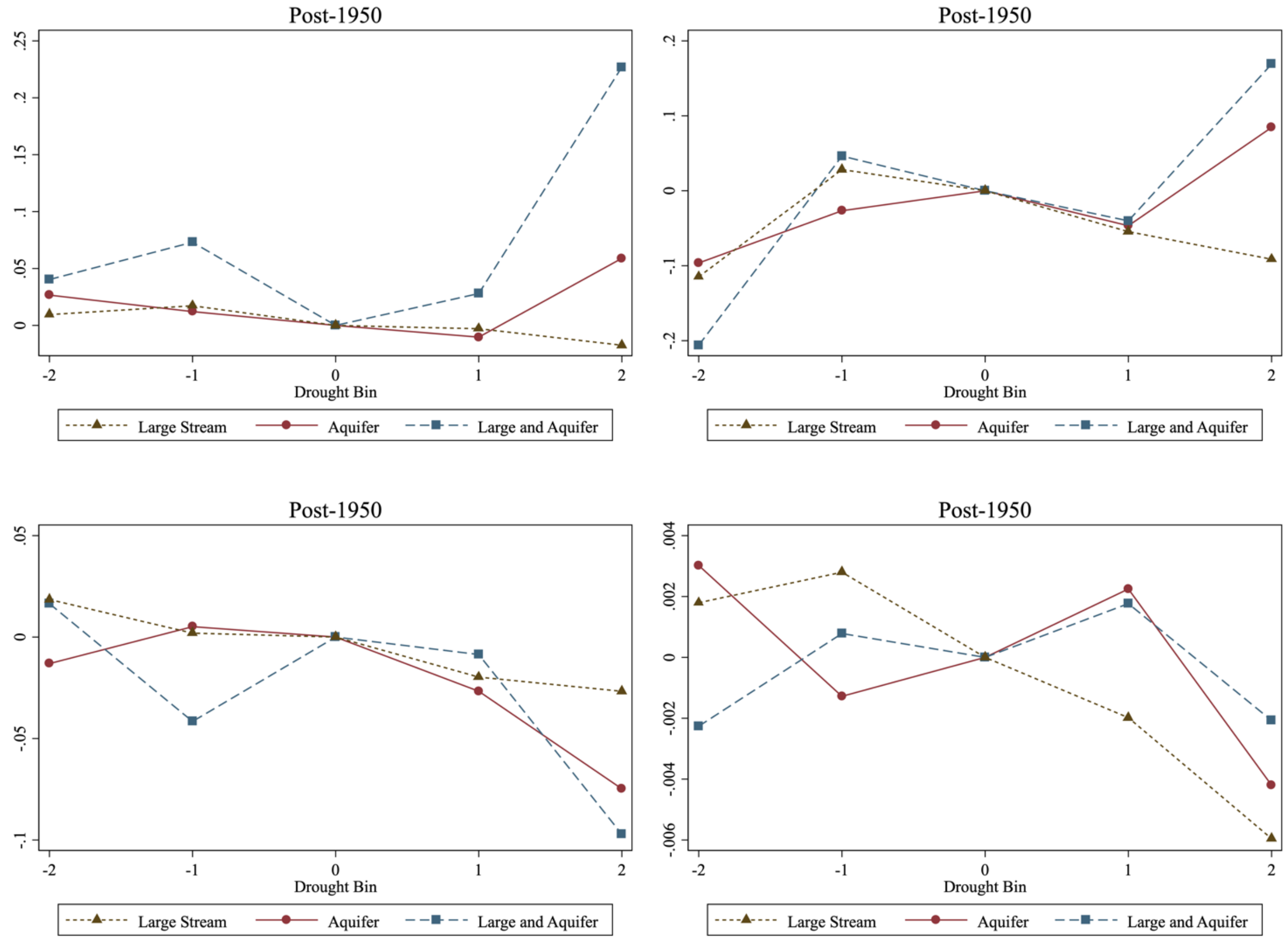
EFFECT OF IRRIGATION WATER STORAGE ON CROPS PLANTED BY PRECIPITATION CONDITIONS



Notes: Coefficient estimates of equation 1. Top-left: Soy, top-right: Corn, bottom-left: Wheat: bottom-right: Hay. The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).

Sources: Authors' estimation; see text.

FIGURE 9
EFFECT OF IRRIGATION WATER STORAGE ON CROPS PLANTED BY PRECIPITATION CONDITIONS

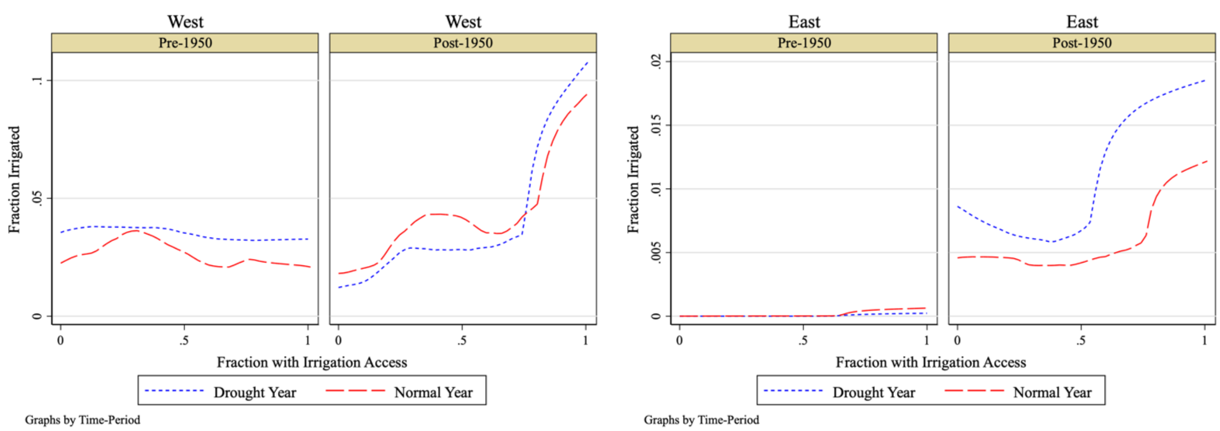


Notes: Coefficient estimates of equations 1 and 2. Top-right: Soy, top-left: Corn, bottom-left: Wheat: bottom-right: Hay. The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).
Sources: Authors' estimation; see text.

4. Discussion

Irrigation has played a significant role in the overall agricultural growth of US Agriculture (Edwards and Smith 2018). For the arid west, it allowed for the expansion of production, particularly following increased access to groundwater and surface water storage. Our focus in this paper is not on these average changes, but on the resilience to weather shocks, controlling for the gains in average production irrigation provided over time. We find that irrigators with access to stored water maintain their own buffer, permitting response to drought conditions. Figure 10 (panel A on the left) shows counties with more access to water storage irrigate more land after 1950 under normal precipitation conditions, but are still able to add to irrigated acres during drought. The flexibility of irrigators with access to storage to increase irrigation is driven by groundwater users.

FIGURE 10
FRACTION IRRIGATED BY EAST/WEST, IRRIGATION ACCESS, AND PRECIPITATION CONDITIONS.



Notes: Local polynomial of the fraction of the county irrigated and the fraction of the county with access to an aquifer or within 15 miles of a large stream (or both). Drought is being below 1.5 standard deviations of the county's historical precipitation distribution. Panel A on the left shows the response for irrigated counties west of the 98th meridian. Panel B on the right shows the response for counties east of the 98th Meridian.
Sources: Authors' rendering of data; see text.

Evidence of this flexibility in the west may be indicative of the gains of irrigation in the east, where conditions do not require irrigation on average and the systems are being adopted to serve as a buffer to increased variance in temperature and precipitation. Though absolute values are still smaller, Figure 10 (panel B on the right) shows that the East has been making similar but even more pronounced adjustments in irrigated acres in response to drought since 1950.

Meanwhile, the lack of flexibility for surface water sources in the west may indicate the need to reconsider how water rights and land are treated. Although access to large streams with dams reduced the loss in irrigated acres relative to the losses experienced by small stream areas considerably, this did not result in statistically significant higher crop revenue for large stream areas. If resiliency is or becomes a key consideration in the allocation of water in the west, thought should be given to the underlying property rights that affect allocations of water from large streams. Rather than applying more water to the same land, as appropriative surface water rights typically require, stored water would be more useful if it could be used on otherwise non-irrigated land in abnormally dry years.

References

Burke, M. and K. Emerick. 2016. Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3), p 106-40

Dell, M., Jones, B.F. and Olken, B.A., 2012. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), pp.66-95.

Dell, M., Jones, B.F. and Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature,* 52(3), pp.740-98.

Deschênes, O. and Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1), pp.354-385.

Deschênes, O. and Greenstone, M., 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4), pp.152-85.

Edwards, E.C. and Smith, S.M., 2018. The Role of Irrigation in the Development of Agriculture in the United States. *The Journal of Economic History*, 78(4), pp.1103-1141.

Feng, S., Oppenheimer, M. and Schlenker, W., 2012. Climate change, crop yields, and internal migration in the United States (No. w17734). National Bureau of Economic Research.

Hagerty, N. 2019. The scope for climate adaptation: Evidence from water scarcity in irrigated agriculture. *Working paper.*

Haines, Michael, Fishback, Price, and Rhode, Paul. United States Agriculture Data, 1840 - 2012. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2018-08-20. https://doi.org/10.3886/ICPSR35206.v4

Hansen, Z.K. and Libecap, G.D., 2004. Small farms, externalities, and the Dust Bowl of the 1930s. *Journal of Political Economy*, 112(3), pp.665-694.

Hansen, Z.K., Libecap, G.D. and Lowe, S.E., 2011. Climate variability and water infrastructure: historical experience in the Western United States. In The economics of climate change: Adaptations past and present (pp. 253-280). University of Chicago Press.

Hornbeck, R. and Keskin, P., 2014. The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, 6(1), pp.190-219.

Hornbeck, R. and Keskin, P., 2015. Does agriculture generate local economic spillovers? Short-run and long-run evidence from the Ogallala Aquifer. *American Economic Journal: Economic Policy,* 7(2), pp.192-213.

Hornbeck, R., 2012. The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review*, 102(4), pp.1477-1507.

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B. and Vail, P., 2018. Estimating the Impact of Drought on Agriculture Using the US Drought Monitor. *American Journal of Agricultural Economics*, 101(1), pp.193-210.

Mendelsohn, R., Nordhaus, W.D. and Shaw, D., 1994. The impact of global warming on agriculture: a Ricardian analysis. *American Economic Review*, 84(4), pp.753-771.

Minnesota Population Center. 2006. Historic Counties for the 1910-2010 Census of Population: vector digital data. Minneapolis, Minnesota. http://www.nhgis.org

National Atlas of the United States. 2014. 1:1,000,000-Scale Hydrographic Geodatabase of the United States—Conterminous United States: Vector digital data. Rolla, MO. http://nationalatlas.gov/atlasftp-1m.html

Pfeiffer, L. and Lin, C.Y.C., 2014. Does efficient irrigation technology lead to reduced groundwater extraction? Empirical evidence. *Journal of Environmental Economics and Management*, 67(2), pp.189-208.

PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created 4 Feb 2004.

Schlenker, W. and Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37), pp.15594-15598.

Schlenker, W., Hanemann, W.M. and Fisher, A.C., 2005. Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1), pp.395-406.

Strzepek, K., Yohe, G., Neumann, J. and Boehlert, B., 2010. Characterizing changes in drought risk for the United States from climate change. *Environmental Research Letters,* 5(4), p.044012.

Tack, J., A. Barkley, and N. Hendricks. 2017. Irrigation offsets wheat yield reductions from warming temperatures. *Environmental Research Letters*, 12(11), p. 114027.

Troy, T.J., Kipgen, C. and Pal, I., 2015. The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters*, 10(5), p. 054013.

USDA, 2019. Census Data Query Tool. URL: https://www.nass.usda.gov/Quick_Stats/CDQT/chapter/1/table/1

USGS. 2003. Principal Aquifers of the 48 Conterminous United States, Hawaii, Puerto Rico, and the U.S. Virgin Islands: digital data. Reston, Virginia. http://water.usgs.gov/lookup/getspatial?aquifers_us

Zaveri, E. and Lobell, D.B., 2019. The role of irrigation in changing wheat yields and heat sensitivity in India. *Nature communications*, 10(1), pp.1-7.

Zhang, T. and Lin, X., 2016. Assessing future drought impacts on yields based on historical irrigation reaction to drought for four major crops in Kansas. *Science of the Total Environment*, 550, pp.851-860.

Supplemental Material

TABLE A1

Drought and Irrigated Acres in the East

VARIABLES	(1) Change in Fraction Irrigated	(2) Change in Fraction Irrigated
Average Drought Bin (1-5)	0.000448***	
	(0.000124)	
Severe Drought Experienced (=1)		0.000334***
		(0.000114)
Observations	35,487	35,487
R-squared	0.009	0.008

Outcome variable for the change in the fraction irrigated between censuses. Average drought bin captures the prior 5 years' average drought bin. Severe Drought indicates at least 1 year in the most severe drought category in last 5 years. Robust standard errors, clustered by county, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE A2

Robustness to Drought Pre-1950

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ln(crops per acre)				
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	0.217**	0.00420	0.0174*	0.00503	0.0400	7.31e-05	-0.0484	-0.00196**
	(0.107)	(0.00394)	(0.0105)	(0.00457)	(0.0382)	(5.43e-05)	(0.0357)	(0.000940)
Above	0.0407	0.00392	0.0328***	0.00810**	0.00177	4.76e-05**	0.0121	-0.00119
	(0.0920)	(0.00327)	(0.0112)	(0.00374)	(0.0225)	(1.85e-05)	(0.0331)	(0.00166)
Below	-0.238***	-0.00130	0.0196	-0.00361	-0.0164	-5.88e-06	-0.0195	-0.00255**
	(0.0781)	(0.00196)	(0.0137)	(0.00315)	(0.0192)	(1.87e-05)	(0.0302)	(0.00116)
Significantly Below	-0.187	-0.00488**	0.0236	-0.00654**	0.0383*	1.31e-05	-0.0313	-0.00261*
	(0.119)	(0.00226)	(0.0160)	(0.00286)	(0.0219)	(1.93e-05)	(0.0336)	(0.00148)
Storage County x.								
Precipitation Bin (normal omitted)								
Significantly Above	-0.355***	-0.00503	0.0182	-0.00785	-0.106**	-5.48e-05	-0.0991**	-0.000512
	(0.137)	(0.00425)	(0.0122)	(0.00516)	(0.0441)	(5.72e-05)	(0.0459)	(0.00140)
Above	-0.0357	-0.00427	-0.00540	-0.00717	-0.0667**	-6.13e-06	-0.00596	0.000184
	(0.109)	(0.00359)	(0.0123)	(0.00436)	(0.0286)	(3.79e-05)	(0.0417)	(0.00192)
Below	-0.0254	-0.00104	0.00747	-0.00774**	-0.112***	-2.06e-05	-0.0705*	-8.95e-05
	(0.0895)	(0.00237)	(0.0142)	(0.00372)	(0.0270)	(2.36e-05)	(0.0363)	(0.00129)
Significantly Below	-0.176	0.00418	0.0205	-0.00752**	-0.0339	-3.14e-05*	-0.105**	-0.00137
	(0.127)	(0.00277)	(0.0178)	(0.00335)	(0.0296)	(1.82e-05)	(0.0413)	(0.00175)
Observations	1,914	1,914	958	1,914	1,914	958	1,914	1,914
R-squared	0.272	0.085	0.271	0.290	0.182	0.018	0.166	0.063
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Storage county is an indicator variable for the county having greater than the 25th percentile of access to aquifers, large streams, or both. Robust standard errors, clustered by county, in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A3

Robustness to Drought Post-1950

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ln(crops per acre)				
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	-0.0931	-0.0114***	0.00191***	-0.00442	-0.121***	-0.0205**	-0.0816***	0.000465
	(0.0742)	(0.00215)	(0.000614)	(0.00295)	(0.0317)	(0.00939)	(0.0201)	(0.00166)
Above	0.0356	-0.00451***	0.00121	-0.00300*	-0.0395	-0.00378	-0.0542**	0.00111
	(0.0372)	(0.00137)	(0.00136)	(0.00178)	(0.0251)	(0.00838)	(0.0210)	(0.000852)
Below	-0.00928	0.000158	0.000180	-0.000938	-0.0220	-0.00428	-0.00578	0.000574
	(0.0336)	(0.00125)	(0.000512)	(0.00160)	(0.0148)	(0.00467)	(0.0126)	(0.000942)
Significantly Below	-0.136*	-0.0136***	0.00173	-0.0164***	-0.146***	-0.0199*	-0.0457**	0.000314
	(0.0696)	(0.00254)	(0.00190)	(0.00318)	(0.0260)	(0.0115)	(0.0225)	(0.000688)
Storage County x.								
Precipitation Bin (normal omitted)								
Significantly Above	0.0824	-8.57e-05	-0.000759	0.00578*	-0.00905	0.0481***	0.0826***	0.00429*
	(0.0799)	(0.00352)	(0.000909)	(0.00340)	(0.0392)	(0.0154)	(0.0254)	(0.00231)
Above	-0.0214	0.00144	-0.000813	0.00307	0.0444	0.0348***	0.0448*	0.000707
	(0.0417)	(0.00209)	(0.00159)	(0.00206)	(0.0301)	(0.0123)	(0.0237)	(0.00115)
Below	0.0168	-0.00106	0.00279***	0.00237	-0.0243	0.00621	-0.0147	0.000795
	(0.0378)	(0.00180)	(0.000890)	(0.00196)	(0.0219)	(0.00863)	(0.0152)	(0.00120)
Significantly Below	0.174**	0.0233***	0.00175	0.0127***	0.231***	0.120***	-0.0285	0.000844
	(0.0772)	(0.00419)	(0.00243)	(0.00331)	(0.0387)	(0.0275)	(0.0259)	(0.000760)
Observations	7,545	7,646	5,738	7,646	7,646	7,646	7,646	7,646
R-squared	0.333	0.142	0.091	0.411	0.273	0.121	0.321	0.046
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Storage county is an indicator variable for the county having greater than the 25th percentile of access to aquifers, large streams, or both. Robust standard errors, clustered by county, in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A4

Robustness to Drought Post-1950

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ln(crops per acre)				
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	-0.118	-0.0106***	0.00266**	-0.00703*	-0.180***	-0.0693***	-0.142***	-0.00235
	(0.109)	(0.00391)	(0.00109)	(0.00401)	(0.0457)	(0.0193)	(0.0273)	(0.00239)
Above	0.110**	-0.00460*	0.00199	-0.00527**	-0.0880**	-0.0376***	-0.0822***	0.000879
	(0.0552)	(0.00247)	(0.00159)	(0.00260)	(0.0364)	(0.0131)	(0.0263)	(0.00119)
Below	0.00737	0.00104	-0.00232**	-0.00404*	-0.0328	-0.0163	-0.0104	-0.000962
	(0.0511)	(0.00217)	(0.000936)	(0.00233)	(0.0256)	(0.0101)	(0.0169)	(0.00123)
Significantly Below	-0.280***	-0.0279***	-0.00211	-0.0226***	-0.336***	-0.133***	-0.0593**	-0.000163
	(0.0913)	(0.00446)	(0.00221)	(0.00372)	(0.0462)	(0.0299)	(0.0253)	(0.000845)
Irrigation Access x								
Precipitation Bin (normal omitted)								
Significantly Above	0.119	-0.00120	-0.00186	0.00928*	0.0680	0.113***	0.164***	0.00814**
	(0.130)	(0.00754)	(0.00183)	(0.00515)	(0.0680)	(0.0338)	(0.0396)	(0.00375)
Above	-0.117*	0.00156	-0.00183	0.00605*	0.107**	0.0787***	0.0818**	0.00103
	(0.0672)	(0.00430)	(0.00228)	(0.00339)	(0.0503)	(0.0217)	(0.0337)	(0.00184)
Below	-0.00406	-0.00221	0.00615***	0.00654**	-0.00999	0.0224	-0.00859	0.00286
	(0.0624)	(0.00357)	(0.00165)	(0.00321)	(0.0420)	(0.0187)	(0.0232)	(0.00184)
Significantly Below	0.361***	0.0424***	0.00683*	0.0211***	0.481***	0.269***	-0.0116	0.00155
	(0.112)	(0.00764)	(0.00369)	(0.00478)	(0.0711)	(0.0558)	(0.0347)	(0.00109)
Observations	7,545	7,646	5,738	7,646	7,646	7,646	7,646	7,646
R-squared	0.334	0.143	0.092	0.412	0.275	0.124	0.321	0.046
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Irrigation access is the fraction of county overlaying an aquifer or within 15 miles of a large stream (or both).
Robust standard errors, clustered by county, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE A5

Robustness to Drought Pre-1950

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ln(crops per acre)				
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	0.216**	0.00420	0.0173	0.00508	0.0404	7.28e-05	-0.0488	-0.00198**
	(0.108)	(0.00395)	(0.0105)	(0.00456)	(0.0384)	(5.45e-05)	(0.0362)	(0.000947)
Above	0.0399	0.00393	0.0329***	0.00817**	0.00285	4.78e-05**	0.0108	-0.00122
	(0.0923)	(0.00327)	(0.0113)	(0.00375)	(0.0226)	(1.86e-05)	(0.0332)	(0.00167)
Below	-0.238***	-0.00130	0.0192	-0.00353	-0.0161	-7.03e-06	-0.0189	-0.00254**
	(0.0784)	(0.00196)	(0.0138)	(0.00316)	(0.0192)	(1.88e-05)	(0.0302)	(0.00116)
Significantly Below	-0.187	-0.00488**	0.0232	-0.00644**	0.0386*	1.21e-05	-0.0305	-0.00258*
	(0.119)	(0.00226)	(0.0161)	(0.00286)	(0.0220)	(1.94e-05)	(0.0338)	(0.00148)
Aquifer County x Precipitation Bin (normal omitted)								
Significantly Above	-0.471***	-0.00695	0.0130	-0.00132	-0.0973**	-6.14e-05	-0.160***	-0.00259
	(0.164)	(0.00450)	(0.0134)	(0.00571)	(0.0476)	(5.71e-05)	(0.0582)	(0.00177)
Above	-0.117	-0.00376	-0.00585	-0.00542	-0.0512	7.65e-06	-0.0881**	-0.000991
	(0.130)	(0.00382)	(0.0127)	(0.00472)	(0.0312)	(5.24e-05)	(0.0419)	(0.00198)
Below	-0.0301	0.000135	0.00779	-0.00403	-0.0888***	-3.29e-05	-0.0815**	0.000898
	(0.103)	(0.00270)	(0.0146)	(0.00412)	(0.0280)	(2.14e-05)	(0.0400)	(0.00132)
Significantly Below	-0.201	0.00268	0.0261	-0.00464	-0.0432	-4.24e-05**	-0.0873*	-0.000154
	(0.139)	(0.00293)	(0.0194)	(0.00372)	(0.0283)	(1.87e-05)	(0.0464)	(0.00178)
Large Stream County x Precipitation Bin (normal omitted)								
Significantly Above	-0.297	-0.00107	0.0340**	-0.0198***	-0.0569	9.96e-05	-0.0374	0.000376
	(0.303)	(0.00495)	(0.0155)	(0.00618)	(0.0612)	(0.000102)	(0.0723)	(0.00260)
Above	0.241**	-0.00418	0.00813	-0.00503	0.00526	-6.11e-05	0.259***	-0.000433
	(0.121)	(0.00463)	(0.0151)	(0.00651)	(0.0545)	(5.82e-05)	(0.0827)	(0.00317)
Below	0.0180	-0.00115	0.0111	-0.00700	-0.0407	-9.39e-06	-0.000632	-0.00418*
	(0.119)	(0.00276)	(0.0168)	(0.00557)	(0.0550)	(8.68e-05)	(0.0503)	(0.00247)
Significantly Below	-0.0702	0.00208	0.0275	-0.00779	0.0648	-3.45e-05	-0.0621	-0.00502
	(0.146)	(0.00303)	(0.0223)	(0.00552)	(0.0696)	(5.38e-05)	(0.0515)	(0.00347)
Joint County x Precipitation Bin (normal omitted)								
Significantly Above	-0.196	-0.00326	0.0142	-0.0157**	-0.153***	-5.65e-05	-0.0515	0.00284*
	(0.149)	(0.00503)	(0.0137)	(0.00609)	(0.0572)	(5.57e-05)	(0.0502)	(0.00162)
Above	-0.0354	-0.00582	-0.0356	-0.0108*	-0.136***	-1.62e-05	0.000314	0.00326
	(0.123)	(0.00432)	(0.0226)	(0.00592)	(0.0451)	(2.29e-05)	(0.0616)	(0.00283)
Below	-0.0398	-0.00338	-0.000329	-0.0158***	-0.205***	1.26e-06	-0.0915**	0.000571
	(0.101)	(0.00335)	(0.0160)	(0.00543)	(0.0470)	(1.77e-05)	(0.0466)	(0.00146)
Significantly Below	-0.179	0.00721*	-0.0159	-0.0121***	-0.0870**	-1.54e-05	-0.120**	-0.000672
	(0.150)	(0.00406)	(0.0178)	(0.00455)	(0.0418)	(1.84e-05)	(0.0573)	(0.00198)
Observations	1,914	1,914	958	1,914	1,914	958	1,914	1,914
R-squared	0.275	0.089	0.282	0.296	0.192	0.025	0.181	0.080
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Aquifer, large stream, and joint county is an indicator variable for whether the greatest share of he county has access to that water type respectively. The baseline county is one that only has acess to small streams defined as having less than the 25th percentile of access to aquifers, large streams, or both. Robust standard errors, clustered by county, in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A6

Robustness to Drought Post-1950

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						ln(crops per acre)		
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	-0.0924	-0.0113***	0.00190***	-0.00438	-0.120***	-0.0202**	-0.0814***	0.000437
	(0.0743)	(0.00215)	(0.000616)	(0.00295)	(0.0317)	(0.00940)	(0.0201)	(0.00166)
Above	0.0357	-0.00449***	0.00121	-0.00300*	-0.0394	-0.00355	-0.0541**	0.00110
	(0.0372)	(0.00137)	(0.00136)	(0.00178)	(0.0251)	(0.00839)	(0.0210)	(0.000852)
Below	-0.00949	0.000169	0.000205	-0.000941	-0.0218	-0.00421	-0.00585	0.000587
	(0.0336)	(0.00126)	(0.000508)	(0.00161)	(0.0148)	(0.00467)	(0.0126)	(0.000942)
Significantly Below	-0.136*	-0.0136***	0.00179	-0.0164***	-0.145***	-0.0193*	-0.0462**	0.000375
	(0.0697)	(0.00253)	(0.00190)	(0.00318)	(0.0260)	(0.0115)	(0.0225)	(0.000684)
Aquifer County x								
Precipitation Bin (normal omitted)								
Significantly Above	0.141	-0.00175	-0.00242*	0.00740*	0.0237	0.0469**	0.0683**	0.00817**
	(0.0862)	(0.00547)	(0.00131)	(0.00392)	(0.0478)	(0.0206)	(0.0291)	(0.00325)
Above	-0.0516	-0.00149	-0.00283	0.00172	0.0128	0.0157	0.0593**	0.00197
	(0.0458)	(0.00281)	(0.00193)	(0.00232)	(0.0357)	(0.0132)	(0.0262)	(0.00151)
Below	-0.0113	-0.00171	0.00431***	0.00319	-0.0248	-0.00610	-0.0208	0.00310**
	(0.0408)	(0.00222)	(0.00137)	(0.00228)	(0.0279)	(0.0110)	(0.0173)	(0.00157)
Significantly Below	0.186**	0.0191***	0.00389	0.0122***	0.230***	0.0782***	-0.0286	0.00198**
	(0.0876)	(0.00454)	(0.00317)	(0.00328)	(0.0489)	(0.0252)	(0.0285)	(0.000976)
Large Stream County x								
Precipitation Bin (normal omitted)								
Significantly Above	-0.00321	0.00526	-4.53e-05	0.00618	0.00527	0.0298	0.0999**	-0.000734
	(0.0971)	(0.00321)	(0.00112)	(0.00394)	(0.0466)	(0.0248)	(0.0389)	(0.00200)
Above	-0.00204	0.00294*	0.00197	0.00580**	0.0676*	0.0208	0.0561	0.000135
	(0.0580)	(0.00177)	(0.00163)	(0.00259)	(0.0353)	(0.0237)	(0.0353)	(0.00201)
Below	-0.00574	0.00107	-0.000858	-0.00104	-0.0327	0.00130	-0.0139	-0.00382**
	(0.0554)	(0.00179)	(0.000850)	(0.00250)	(0.0272)	(0.00852)	(0.0228)	(0.00191)
Significantly Below	0.0854	0.0112***	-0.000785	0.0105**	0.0539	0.00183	0.0195	-0.000872
	(0.0877)	(0.00353)	(0.00271)	(0.00416)	(0.0445)	(0.0339)	(0.0377)	(0.00112)
Joint County x								
Precipitation Bin (normal omitted)								
Significantly Above	0.0265	-0.000919	0.00270*	0.00212	-0.0860	0.0606**	0.0979***	0.000315
	(0.0924)	(0.00497)	(0.00146)	(0.00463)	(0.0623)	(0.0289)	(0.0374)	(0.00254)
Above	0.0213	0.00567	0.000457	0.00378	0.0857**	0.0766***	0.0126	-0.00130
	(0.0484)	(0.00346)	(0.00210)	(0.00281)	(0.0392)	(0.0212)	(0.0284)	(0.000952)
Below	0.0876*	-0.00125	0.00349**	0.00271	-0.0183	0.0322*	-0.00275	-0.000966
	(0.0452)	(0.00314)	(0.00144)	(0.00300)	(0.0333)	(0.0174)	(0.0205)	(0.00100)
Significantly Below	0.195**	0.0358***	-0.00130	0.0143***	0.314***	0.246***	-0.0510	-0.000235
	(0.0901)	(0.00782)	(0.00238)	(0.00500)	(0.0618)	(0.0657)	(0.0339)	(0.000659)
Observations	7,545	7,646	5,738	7,646	7,646	7,646	7,646	7,646
R-squared	0.334	0.144	0.098	0.412	0.275	0.127	0.322	0.049
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Aquifer, large stream, and joint county is an indicator variable for whether the greatest share of he county has access to that water type respectively. The baseline county is one that only has acess to small streams defined as having less than the 25th percentile of access to aquifers, large streams, or both. Robust standard errors, clustered by county, in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A7

Robustness to Drought Post-1950

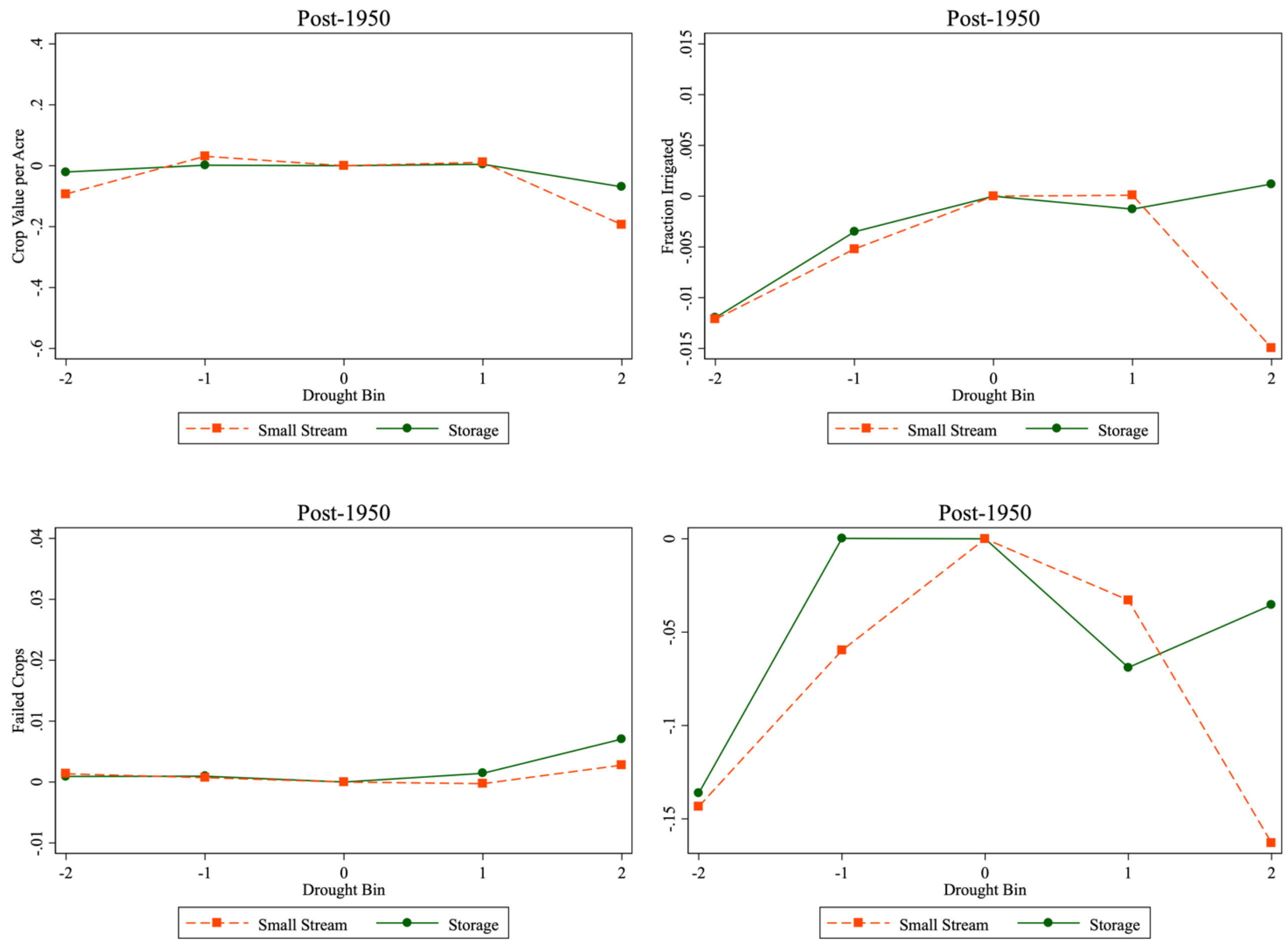
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						ln(crops per acre)		
VARIABLES	ln(Crop Value per Acre)	Fraction Irrigated	Failed Crops per Acre	Hay	Corn	Soy	Wheat	Cotton
Precipitation Bin (normal omitted)								
Significantly Above	-0.107	-0.0119***	0.00240*	-0.00826**	-0.232***	-0.0582***	-0.137***	-0.00364
	(0.114)	(0.00431)	(0.00134)	(0.00411)	(0.0472)	(0.0221)	(0.0287)	(0.00254)
Above	0.111*	-0.00338	0.00300*	-0.00653**	-0.0727*	-0.0159	-0.0861***	-7.51e-05
	(0.0577)	(0.00252)	(0.00160)	(0.00264)	(0.0375)	(0.0138)	(0.0272)	(0.00140)
Below	0.0301	0.000369	-0.00386***	-0.00308	-0.0180	-0.00473	-0.00201	-0.000741
	(0.0530)	(0.00214)	(0.00107)	(0.00236)	(0.0266)	(0.00944)	(0.0174)	(0.00144)
Significantly Below	-0.253***	-0.0216***	-0.00223	-0.0219***	-0.264***	-0.0625***	-0.0742***	-0.000483
	(0.0951)	(0.00384)	(0.00230)	(0.00373)	(0.0411)	(0.0225)	(0.0245)	(0.000944)
Aquifer Access x								
Precipitation Bin (normal omitted)								
Significantly Above	0.190	-0.00261	-0.00544	0.0143**	0.239**	0.0831*	0.111**	0.0208***
	(0.148)	(0.0130)	(0.00331)	(0.00592)	(0.0929)	(0.0493)	(0.0521)	(0.00694)
Above	-0.173**	-0.00789	-0.00652*	0.00625*	0.00250	0.00184	0.0832**	0.00556*
	(0.0760)	(0.00606)	(0.00343)	(0.00370)	(0.0662)	(0.0227)	(0.0393)	(0.00303)
Below	-0.0855	-0.00248	0.0138***	0.00634*	-0.0675	-0.0256	-0.0487*	0.00751**
	(0.0731)	(0.00474)	(0.00300)	(0.00360)	(0.0581)	(0.0253)	(0.0281)	(0.00321)
Significantly Below	0.329**	0.0269***	0.0136**	0.0173***	0.369***	0.0840	-0.00917	0.00480***
	(0.136)	(0.00893)	(0.00584)	(0.00479)	(0.0901)	(0.0529)	(0.0440)	(0.00181)
Large Stream Access x								
Precipitation Bin (normal omitted)								
Significantly Above	-0.0276	0.0118	0.00344	0.0141	0.311***	0.0751	0.196**	0.00355
	(0.215)	(0.00802)	(0.00440)	(0.00861)	(0.113)	(0.0870)	(0.0804)	(0.00385)
Above	-0.0732	0.00352	-0.00406	0.0144***	0.110*	0.0127	0.109	0.00210
	(0.111)	(0.00402)	(0.00400)	(0.00509)	(0.0666)	(0.0551)	(0.0693)	(0.00411)
Below	-0.0919	0.00388	0.0100***	-0.00142	-0.0617	-0.0108	-0.0313	-0.00464
	(0.103)	(0.00363)	(0.00263)	(0.00531)	(0.0576)	(0.0199)	(0.0414)	(0.00377)
Significantly Below	0.198	0.0120*	0.00263	0.0186***	0.0704	-0.0620	0.0920	0.000114
	(0.164)	(0.00663)	(0.00435)	(0.00670)	(0.0834)	(0.0915)	(0.0683)	(0.00214)
Joint Access x								
Precipitation Bin (normal omitted)								
Significantly Above	0.0437	-0.000722	0.00168	0.00393	-0.117	0.137***	0.216***	-0.00415
	(0.140)	(0.00836)	(0.00148)	(0.00690)	(0.0925)	(0.0527)	(0.0515)	(0.00272)
Above	-0.0622	0.0105*	0.00272	0.00609	0.208***	0.150***	0.0804**	-0.00311**
	(0.0716)	(0.00548)	(0.00204)	(0.00455)	(0.0566)	(0.0325)	(0.0392)	(0.00136)
Below	0.0728	-0.00204	-0.000949	0.00661	0.0456	0.0673**	0.0288	-0.00151
	(0.0640)	(0.00483)	(0.00137)	(0.00448)	(0.0510)	(0.0275)	(0.0280)	(0.00139)
Significantly Below	0.377***	0.0541***	0.000153	0.0245***	0.556***	0.415***	-0.00855	-0.00106
	(0.115)	(0.0103)	(0.00365)	(0.00700)	(0.0823)	(0.0882)	(0.0446)	(0.000846)
Observations	7,545	7,646	5,738	7,646	7,646	7,646	7,646	7,646
R-squared	0.335	0.146	0.109	0.412	0.279	0.134	0.322	0.052
Number of County	479	479	479	479	479	479	479	479
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Regression estimates for various outcomes per county acre. Precipitation bins are locally defined and the normal bin (-0.5 to 0.5 standard deviations) is omitted category. Significantly above (below) is beyond 1.5 standard deviations. Aquifer access is the fraction of county overlaying an aquifer, large stream is the fraction within 15 miles of a large stream, and joint access is the fraction over an aquifer and within 15 miles of a large stream. Robust standard errors, clustered by county, in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

FIGURE A1

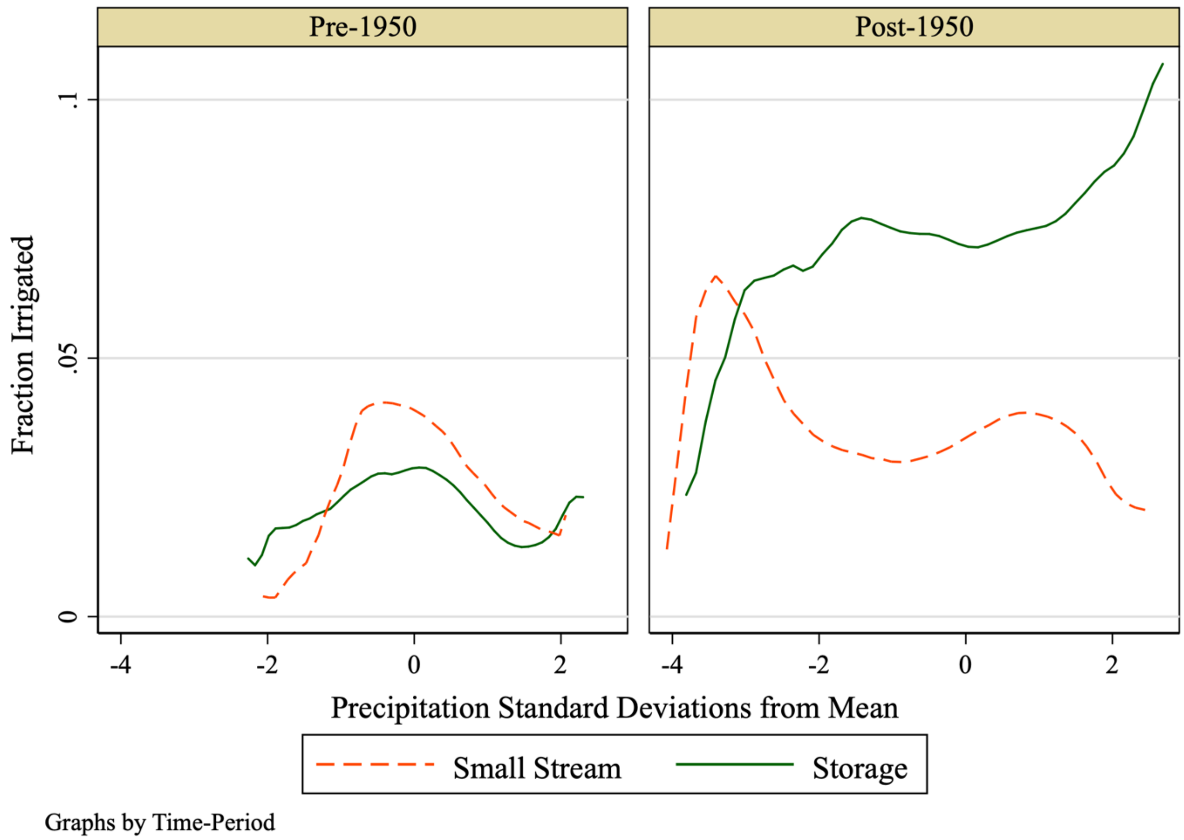
EFFECT OF IRRIGATION WATER STORAGE ON AGRICULTURE ECONOMICS, WITHOUT 2012, BY PRECIPITATION CONDITIONS



Notes: Coefficient estimates of equations 1. Top-left: Crop Value, top-right: Fraction Irrigated, bottom-left: Failed crops: bottom-right: ln(harvested corn acres(. The estimates represent deviations from a county's average relative to normal levels of precipitation (bin 0), bins 1 and 2 indicate more severe droughts (less precipitation).

Sources: Authors' estimation; see text.

FIGURE A2
FRACTION IRRIGATED BY STORAGE ACCESS AND PRECIPITATION CONDITIONS.



Notes: Local polynomial of the fraction of the county irrigated and the number of standard deviations from the county's precipitation mean. Larger numbers are calibrated to indicate a more severe drought (less rain). Storage counties are defined as those with at least 56 percent of the county overlaying an aquifer, within 15-miles of a large stream, or both.
Sources: Authors' rendering of data; see text.

FIGURE A3
DEVIATION IN FRACTION IRRIGATED BY IRRIGATION ACCESS TYPE