External Costs of Climate Change Adaptation: Agricultural Wells and Access to Drinking Water*

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Abstract

Actions to mitigate the costs of climate change may exacerbate existing externalities. We study this in the context of groundwater in California, an open-access resource, by evaluating if averting behaviors taken in response to annual fluctuations in local heat and surface water scarcity lead to groundwater depletion and drinking well failures. Using the population of geocoded groundwater wells, we find that the surface water reductions and extreme heat experienced in 2021 lowered the groundwater table by 2 feet and 8 inches, respectively. This leads to drinking well failures in disadvantaged communities, with surface water curtailments and heat increasing failures by 4 and 5 percentage points. We show that agricultural groundwater pumping and well construction drive these external costs. These findings highlight that open-access management of groundwater may exacerbate inequities in the ability of disadvantaged communities and future generations to buffer against weather shocks.

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1 Introduction

The direct costs of climate change are expected to be large in magnitude and broad in reach, affecting agriculture, economic growth, migration, labor productivity, and mortality (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005; Deschenes and Kolstad, 2011; Schlenker and Roberts, 2009; Dell, Jones, and Olken, 2012; Lobell, 2014; Graff Zivin and Neidell, 2014). Averting behaviors may lessen some contemporaneous costs and allow for adaptation to climate change in the longer term (Barreca et al., 2016; Burke and Emerick, 2016). However, these actions themselves may impose externalities that are disproportionately borne by those unable to engage in mitigating behavior. Little is known about the extent to which avoidance behaviors taken to reduce the damages of weather shocks impose costs on others.

We study this in the context of groundwater in California by evaluating if mitigating behaviors taken in response to heat and surface water scarcity lead to groundwater depletion and drinking water well failures. Agriculture is almost exclusively irrigated in California, and farmers rely on surface water supplies conveyed via canals and rivers and groundwater pumped from wells. Groundwater has operated as a critical mitigation strategy to temper the agricultural costs of surface water reductions and heat (Schlenker, Hanemann, and Fisher, 2005, 2007; Edwards and Smith, 2018). It also has been historically unregulated with poorly defined property rights and little to no quantity restrictions, leading to over-extraction (Ayres, Meng, and Plantinga, 2021). Dependence on this common-pool resource during times of scarcity may impose costs on both current and future users.

To date, the focus of groundwater externalities has either been in the theoretical domain or on quantifying the pumping and stock externality imposed upon neighboring and future agricultural users.[1] Less well understood are the acute and contemporaneous costs that groundwater

[1] A declining water table may impose a pumping cost externality which makes groundwater irrigation costlier for neighboring farms and a stock externality which makes it unavailable to farmers in the future (Provencher and Burt, 1993; Roseta-Palma, 2002; Brozović, Sunding, and Zilberman, 2010; Pfeiffer and Lin, 2012; Edwards, 2016; Merrill and Guilfoos, 2017).

pumping may exact on drinking water supplies in surrounding communities. Many rural households rely on private domestic groundwater wells for drinking water purposes. Relative to their agricultural counterparts, domestic wells are shallow and as a result susceptible to running dry as groundwater tables decline. In California, domestic wells are also concentrated in disadvantaged communities comprised of low-income households and people of color.[2] Access to drinking water supplies among disadvantaged communities is a growing concern, and it remains unanswered how drought- and heat-induced groundwater pumping jeopardizes drinking water availability (Pauloo et al., 2020).

This paper quantifies how groundwater extraction by farmers, in response to annual fluctuations in heat and surface water scarcity, impacts the depth to the groundwater table and access to drinking water for domestic well owners. Our conceptual framework posits that surface water curtailments and heat will induce agricultural users to respond on the intensive and extensive margins, extracting more water from existing wells and building new and deeper groundwater irrigation wells. These responses will impact access to drinking water supplies through the channel of groundwater scarcity. We empirically test these hypotheses by first capturing the gross effect of these shocks on agricultural groundwater demand as measured by changes in the depth to the water table. Then, we evaluate the reduced-form relationship of heat and surface water scarcity on domestic well failures, assuming this operates through the channel of groundwater table depletion. Finally, we evaluate agricultural producers' extensive margin of response through the drilling of new groundwater wells and back out the intensive margin of response.

Our empirical approach uses year-to-year variation in local surface water curtailments and weather to compare drinking and agricultural water access under various weather shocks. To do this, we build a geocoded well-level data set spanning 28 years that is comprised of more than 180,000 domestic and agricultural wells and, on average, about 20,000 groundwater monitoring

[2]California's San Joaquin Valley contains the majority of domestic wells in the state. It is a region that is over 50% Latina/o and contains some of the highest rates of poverty and food insecurity in the state.

wells per year. We combine these data with district-level weather and surface water allocation data from over 400 regions between 1993 and 2020. These detailed data allow us to deploy an instrumental variable panel data approach that exploits annual fluctuations in temperature and surface water supplies, and controls for local fixed differences such as historical water rights and state level shocks such as recessions that likely impact water access and agricultural producers' decision making.

A first set of results indicates that reductions in agricultural surface water supplies and extreme heat lower the depth to the groundwater table. A recent drought in 2021 caused surface water supplies to reduce by as much as 0.7 acre-feet (AF) per crop acre. Our results indicate that an annual surface water curtailment of this size would cause a 2-foot reduction in groundwater levels across California's aquifers. A similar effect is found for cumulative days of extreme heat. Heat shocks, equal to 2021 levels (an additional 23 harmful degree days), caused an 8-inch reduction in the groundwater table. These reductions in groundwater availability capture both the private cost incurred by farmers to mitigate the damages from heat and surface water curtailments and the external cost imposed on future and contemporaneous users of this common-pool resource, including households that access drinking water from domestic wells.

A second central result demonstrates that increases in extreme heat and reductions in surface water availability also lead to domestic well failures, with a decrease in surface water supplies and additional heat resulting in 4 and 5 percentage point increase in well-failures, respectively. These results are consistent with a theoretical framework and computational hydrology model in which increased groundwater consumption among agricultural users comes at the cost of drinking water supplies through the channel of a declining water table (Pauloo et al., 2020). We further decompose these effects by demographics and show that low-income and communities of color bear almost the entirety of these well failures and associated costs.

Lastly, we show that these changes are the result of increased groundwater extraction by farmers as they buffer against surface water scarcity and extreme heat. We show that reduction in surface water – equal to 2021 levels – caused farmers to respond through the extensive margin and drill 320 more agricultural groundwater wells in the contemporaneous year. A back-of-the envelope calculation estimates that farmers also respond through the intensive margin by pumping an additional 27.5 AF from each existing well. We also highlight that even if water supplies remain unchanged, warmer temperatures will increase demand for groundwater, with an additional 23 harmful degree days causing farmers to construct 300 additional groundwater wells and pump 12 AF more from existing wells in that year.

These finding brings a new data point on the extent to which adaptation will buffer against the agricultural costs of climate change. Recent work highlights that in long-run the agricultural costs of climate change may be cut in half as producers adapt - through practices such as technology adoption, changes in inputs, and where crops are grown - to warming temperatures and more variable water supplies (Hultgren et al., 2022). However, in the context of California we show that the open-access management of a common-pool resource may result in the opposite being true. In the short-run, heat shocks and surface curtailments will deplete the available groundwater stock, suggesting that in the long-run the costs of climate change may be larger if farmers cannot rely on groundwater to buffer against these shocks (Hornbeck and Keskin, 2014; Auffhammer, 2018; Perez-Quesada, Hendricks, and Steward, 2023). Regulations that seek to remedy inefficiencies attributable to the open access management of the groundwater may allow farmers to continue to use groundwater to mitigate against weather shocks (Ayres, Meng, and Plantinga, 2021).

Our work also adds a new dimension to our understanding about inequities in exposure to environmental costs (Banzhaf, Ma, and Timmins, 2019). A recent literature documents the unequal rate at which disadvantaged communities are exposed to pollution and the relative health costs, as well as the distributional implications of environmental regulations intended to reduce exposure (Bento, Freedman, and Lang, 2015; Shapiro and Walker, 2021; Hernandez-Cortes and Meng, 2023). Our work implies that inequities arise from the absence of regulation, specifically that mitigating behaviors by those with access to capital will impose costs on disadvantaged groups.

When implementing proactive policy aimed at easing the burden of climate change, policymakers must ensure they are not unintentionally burdening the most vulnerable individuals.

2 Agriculture and Rural Communities in California

We study this question in a setting where water is increasingly scarce, and there exists a perpetual tension between agricultural irrigators in California and other water users in the state. Agriculture in California, which is almost entirely irrigated, employs over 400,000 people and generates over $50 billion in agricultural sales, the most of any state in the United States (California Department of Food and Agriculture, 2020). Agricultural production in California is heavily concentrated in the San Joaquin Valley (SJV) in central California. The counties that comprise the SJV are largely rural and experience some of the highest poverty rates in the country. Many households in these rural areas utilize private domestic wells and depend on groundwater wells for residential use and drinking water supply. The geographic intersection of agricultural groundwater use and groundwater-dependent households makes these areas particularly vulnerable to climate change-driven depletion of groundwater resources.

2.1 Surface Water Irrigation

California experiences substantial inter-annual variability in surface water supplies. Summertime surface water availability in California is largely determined by the previous winter's snowfall. As the Sierra Nevada snowpack melts, it is captured in reservoirs and later delivered to farmers and irrigation districts through a network of canals. Swings between dry and wet winters in California translate to significant variation in surface water supplies from year-to-year.

Surface water in California is allocated through a mixture of appropriative water rights and long-term contracts, which have been in place since the early 1900s. A water user or entity will either hold an appropriative right to divert water directly from a river to a nearby field, or alternatively, they may possess a long-term contract to water deliveries through canals operated by the State Water Project or the federal Central Valley Project.[3] Most water rights and contracts are held by irrigation districts – local government agencies – which then supply water to farms within their jurisdiction. Water is typically rationed by quantity rather than price, and by custom or law water is distributed uniformly to producers on a per-acre basis within a district. This scheme of rights and contracts introduces significant variation in surface water availability across districts, even within the same year.

During times of drought, surface water is allocated through water rights and contracts through a first-in-time, first-in-right system. This leads to variation in surface water allocations across time and space as weather shocks occur. Each district's allocation amount is announced prior to the growing season, before farmers make input decisions, and is based on that year's expected reservoir levels. Thus, this variation in allocation is largely independent of local weather conditions and farmers' choices. However, actual surface water deliveries can differ from allocations in a few ways. Irrigation districts can purchase additional water mid-season on the spot market, pump water from groundwater banks, or reserve water for up to a year in response to environmental conditions.

2.2 Groundwater Irrigation

Groundwater has traditionally acted as a buffer to fluctuations in surface water supply, accounting for 80% of water supplies during times of drought. Changes in surface water deliveries are thus correlated with groundwater pumping which affects the water table. Historically, this sector has been largely unregulated. Owners of land have the right to drill wells and pump groundwater with few restrictions. The open-access nature of groundwater has led to declining groundwater levels,

[3]Contracts with the federal and state water projects constitute a maximum annual volume and a contract category. Each year, the U.S. Bureau of Reclamation and the California Department of Water Resources (DWR) announce a set of allocation percentages, which determine how much of their maximum volume contractors in each category will receive. In recent years, it is common for allocation percentages to be set as low as 0% during droughts.

higher costs to pump, and other negative consequences. Some of California's groundwater basins, like those in the San Joaquin Valley, have experienced over 100ft reductions in groundwater levels in the past 10 years (Department of Water Resources, n.d.). As a result, a historic groundwater regulation was passed in 2014 – the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater in California by 2042.[4]

The fixed cost of groundwater well construction varies widely based on the completed drilled depth and intended use. Residential domestic wells are typically between 100 and 300 ft deep and cost approximately $10,000. Agricultural wells are drilled between 300 and 500 ft deep on average and cost about $75,000, but can cost upwards of $300,000 for large wells. They also are drilled with a wider diameter than residential wells to allow for higher flow rates. New wells are required to be reported to the DWR and are typically constructed in under a week (Central Valley Flood Protection Board, 2020).

2.3 Drinking Water in Rural Communities

Most individuals in California receive residential and drinking water from community water systems regulated by the Safe Drinking Water Act (SDWA).[5] However, many individuals outside of community water system boundaries, like households in rural areas, rely on private groundwater wells for their domestic water supply. Figure A1, which maps the location of domestic wells throughout the state, makes clear that many private drinking water wells exist in agricultural centers of the state.[6]

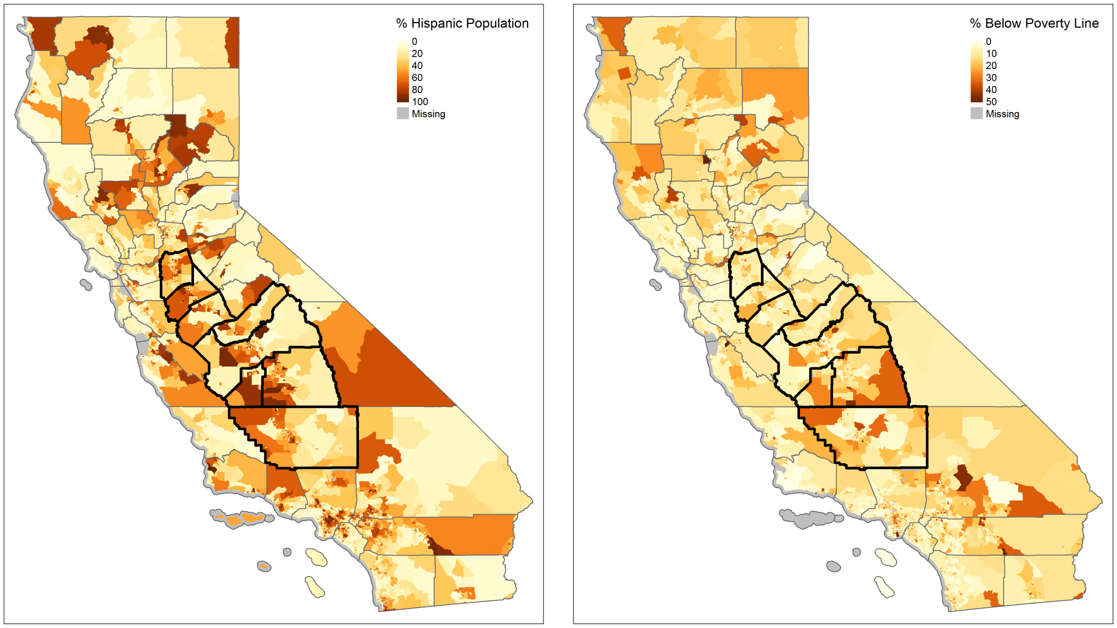
Declining groundwater tables, caused by agricultural extraction, threatens drinking water

[4]Most SGMA sustainability plans were developed and will be enforced by local groundwater sustainability agencies (GSA) starting in 2022, after our sample of study. There remains no direct restrictions on the drilling of groundwater wells in these plans.

[5]By the SDWA definition, community water systems are public water systems with over 15 connections and serve greater than 25 people.

[6]Deteriorating drinking water quality is also pervasive for many of these users, especially since these water sources are outside the jurisdiction of the SDWA.

Figure 1: Population Demographics in California



% Hispanic Population
(a)

% Population below poverty line
(b)

Note: Figure displays demographics at the census tract level using data from 2020 (Manson et al., 2022). Panel (a) plots the percentage of the population that identifies as Hispanic. Panel (b) plots the percentage of households that fall below the federal poverty line for their household size. Bold county boundaries specify counties in the San Joaquin Valley.

access for households that depend on domestic wells for residential water. As groundwater tables decline relative to the depths that wells are drilled, the likelihood of wells running dry increases. Dry wells impose substantial costs on households, either through the costly construction of new, deeper wells or the regular purchasing of alternative water sources, like bottled water.

The burden of groundwater scarcity is bearing out economically and socially vulnerable communities in California. Populations in the San Joaquin Valley are 50.2% Hispanic (national average: 18.9%) and 23.2% of households are below the federal poverty line (national average: 12.9%). Figure 1 shows the spatial variation of these demographics at the census tract level. The location of domestic well failures is also correlated with these demographics. Table 1 reports the proportion of reported well failures as a fraction of the total number of domestic wells by local demographics, agricultural intensity, and well characteristics. Wells in census tracts with above median poverty rates and above median populations of color report well failures at a statistically significant higher rate than tracts below the median. Additionally, areas where land is more highly cultivated for agricultural use also experience well failures at a higher rate.

Table 1: Probability of Well Failure by Local Demographics and Well Characteristics

	(1)	(2)	(3)	(4)
	Below Median	Above Median	Difference	p-value
Poverty Rate	0.0089	0.0346	0.0258	0.0000
% Cropland	0.0091	0.0426	0.0335	0.0000
% Non-White	0.0085	0.0348	0.0263	0.0000
Population	0.0166	0.0305	0.0139	0.0000
Well Depth	0.0249	0.0264	0.0015	0.1793

Note: Columns 1 and 2 display the probability of domestic well failure for all domestic wells in California by socioeconomic, agricultural, and well characteristics. Demographic data come from the USDA Food Research Atlas and are assigned at the census tract levels. Poverty rate is the percent of households living below the Federal income thresholds by family size. Column 3 calculates the difference between the above median probability and below, and Column 4 reports the p-value for a two-sample t-test of the well failure probabilities.

2.4 Impacts of Climate Change in California

Water scarcity in California is expected to only be exacerbated by climate change. While climate models project only modest changes in the mean annual precipitation, the amount of water available in reservoirs and canals for irrigation is expected be reduced by 25% by 2060 (Wang et al., 2018). The latter is, in part, due to increased precipitation volatility and extreme drought risk brought on by climate change (Diffenbaugh, Swain, and Touma, 2015; Swain et al., 2018), and insufficient infrastructure to conserve water in reservoirs in the wettest years. Warming temperatures also increase crop demands for water as an input. Therefore, even if surface water supplies are held constant, farmers will demand more water for irrigation as extreme heat becomes more prevalent (Rosa et al., 2020).

To date, the estimated impacts of climate change on California agriculture are mixed. The earliest estimates ranged from negligible effects to profits of up to 15% (Mendelsohn, Nordhaus, and Shaw, 1994; Deschênes and Greenstone, 2007). Others have estimated negative impacts when accounting for water availability and crop quality, especially among fruits and vegetables (Schlenker, Hanemann, and Fisher, 2007; Smith and Beatty, 2023). Direct climate damages are mitigated through adaptive behaviors by farmers (Burke and Emerick, 2016; Hagerty, 2021), like increased irrigation, and these behaviors may explain why damages were calculated to be minimal in earlier studies. However, these avenues of mitigation may be unavailable in the future either due to groundwater scarcity or regulation that curbs its over-use. This implies that direct climate damages may be significantly worse in the future as water becomes more scarce.

3 Conceptual Model

We develop a conceptual framework to decompose farmers' response to heat and surface water scarcity and the subsequent impacts of this behavior on changes in groundwater levels. The decomposition will reveal the margins of the response and how each channel relates to gross changes in the groundwater level.

Let gross groundwater consumption for a representative farmer, denoted by C, equal the product of the total number of wells, w, and the average amount of water pumped per well, q. Farmers choose the number of wells to construct and how much groundwater to pump from each well. These decisions are functions of both surface water (s) - a substitute for groundwater - and extreme heat (h):

$$C(s,h) = w(s,h) \times q(s,h) \tag{1}$$

Groundwater consumption directly impacts the contemporaneous and future water stock. If total groundwater extraction exceeds recharge then the stock of water in the aquifer declines and the depth to the remaining groundwater stock increases.[7] The depth to the water table (DTW) is given by:

$$DTW(s,h) = DTW_0 + \kappa \times C(s,h), \tag{2}$$

which depends on the baseline depth to the water table, DTW_0, and consumption. The effect of an AF of consumption on depth to the water table directly relates to the geological characteristics of the aquifer that can be captured by a constant multiplier, κ.[8]

Assume that the farmer experiences a surface water (or heat) shock, ds (dh). The gross change in DTW from this shock can be decomposed into two channels:

$$\frac{dDTW}{ds}(s,h) = \kappa\left[\frac{\partial w}{\partial s}(s,h) \times q(s,h) + \frac{\partial q}{\partial s}(s,h) \times w(s,h)\right]. \tag{3}$$

First, farmers may respond through the extensive margin by drilling new irrigation wells $\frac{\partial w}{\partial s}(s,h)$. Second, farmers may react along the intensive margin, extracting more groundwater from existing wells: $\frac{\partial q}{\partial s}(s,h)$.

This conceptual framework provides us with a pathway to empirically recover the intensive and extensive margins of response to surface water and heat shocks. In our empirical model, we directly estimate $\frac{dDTW}{ds}(s,h)$, the change in groundwater levels due to surface water shocks, and the extensive margin, $\frac{\partial w}{\partial s}(s,h)$. We then back out the intensive-margin effect, $\frac{\partial q}{\partial s}(s,h)$, under given

[7] Groundwater aquifers are porous rock and sediment formations that store groundwater. The volume of water an aquifer can hold varies depending on porosity and sediment type. For highly porous aquifers, less total area is required to hold the same amount of water relative to a less porous aquifer.

[8] κ captures the inverse of hydrologic storativity of an aquifer. Storativity measures the hydrologic yield of an aquifer, and hydrologic yield is defined as the proportion of space that water can occupy within an aquifer. As an example, a storativity value of 0.12, which is typical in California's Central Valley Aquifer (Department of Water Resources, 2020), indicates that 12% of the aquifer can hold water. The other 88% is composed of porous rock and sediment.

assumptions.[9] We also compute the analogous decomposition for the effect of a heat shock, dh, on groundwater consumption. This allows us to identify a gross effect of climate shocks as captured by changes in depth to the water table, and decompose the mechanisms behind this effect.

One external damage of declining groundwater tables are well failures. As the water table deepens, shallow drinking water wells may run dry and fail, requiring the well owner to drill new, deeper wells or rely on water from costly alternative sources. Define the probability of well failure, F, as:

$$F = F(DTW) = F(DTW(s,h)) \tag{4}$$

When a surface water shock occurs, there is a change in the probability of well failure :

$$\frac{dF}{ds} = \frac{\partial F}{\partial DTW}\frac{\partial DTW}{\partial s} \tag{5}$$

Empirically, we shed light on the reduced form effect, $\frac{dF}{ds}$, by evaluating the extent to which changes in surface water scarcity and heat lead to a lowering of the groundwater table, and ultimately household well failures.

4 Data

Panel data on surface water deliveries and allocations, groundwater levels, and well construction and failures form the primary dataset for this analysis. We supplement these data with additional information on local weather. Table 2 provides summary statistics.

[9]As discussed in the results, we calculate average values of q and w based on our data and California agricultural statistics, and impose a constant value for κ consistent with California aquifers.

Table 2: Summary Statistics

	Unit	Count	Mean	SD	Min	Max
Outcomes:						
New Ag Wells	DAUCO	10,416	11.1	19.4	0	316
Depth to Groundwater (ft)	Monitoring Well	575,410	62.9	80.4	0	2,714.1
ΔDTW	Monitoring Well	575,399	0.3	6.1	-58.7	56.3
Probability of Domestic Well Failures	Domestic Well	473,940	0.03	0.16	0	1
Independent Variables:						
Ag SW Allocation (AF/crop acre)	DAUCO	9,660	2.3	2.04	0	10
Ag SW Deliveries (AF/crop acre)	DAUCO	10,416	2.2	1.9	0	10
Harmful Degree Days	DAUCO	9,996	97.2	86.9	0	622.3
Growing Degree Days	DAUCO	9,996	3,535.4	659.9	632.5	5,813.04
Annual Precipitation (mm)	DAUCO	9,996	350.3	233.4	11.4	4,668.9
Crop Acres	DAUCO	10,416	169,741.5	131,332.9	.2	502,692.3

Note: The table reports the number of observations, units of and measurement, mean, standard deviations (SD), minimum and maximum for each outcome and explanatory variable. Mean and SD statistics are weighted by crop acres. Water is measured in acre feet (AF).

Surface Water Allocations and Deliveries

Panel data on surface water deliveries and allocations measure our covariate of interest, surface water availability. These data were obtained from Hagerty (2021) and provide yearly measures of water deliveries and allocations from the Central Valley Project (CVP), State Water Project (SWP), Lower Colorado Project, and surface water rights from 1993-2020.[10] We spatially aggregate these data to the Detailed Analysis Unit by County (DAU by Co or DAUCO), and define the DAU as the geographic unit of observation for surface water deliveries, allocations, well construction and well failures. DAUs divide California's hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis by the California Department of Water Resources. Water allocations measure how much water a DAUCO should receive based on rights and contracts, and deliveries reflect how much water a DAUCO actually receives. We transform total water allocations and deliveries by dividing by cropland acres in each DAUCO. Our final measure of surface water supplies captures the volume of surface water delivered in AF per crop

[10]Surface water delivery data for the CVP are first available from the U.S. Bureau of Reclamation in a digitized format in 1993. Therefore, these variables determine the temporal length of our final panel.

acre (AF/acre) in the DAUCO.[11]

Figure 2 displays the variation in surface water allocations across the 390 DAUCOs in three years: 1994, 2006, 2015. In relatively wet years, such as 2006, each DAUCO receives between 80% to 100% of its water allocation. In drought years, such as 1994 and 2015, some DAUCOs experience water curtailments based on contract types and senior rights. This occurs because of weather-induced reductions in surface water availability. This figure makes clear that adjacent water districts can receive very different allocations, and that these differences in allocations vary year-to-year. Our empirical approach will exploit within district variation in surface water availability after netting out aggregate state shocks.

Depth to the Water Table

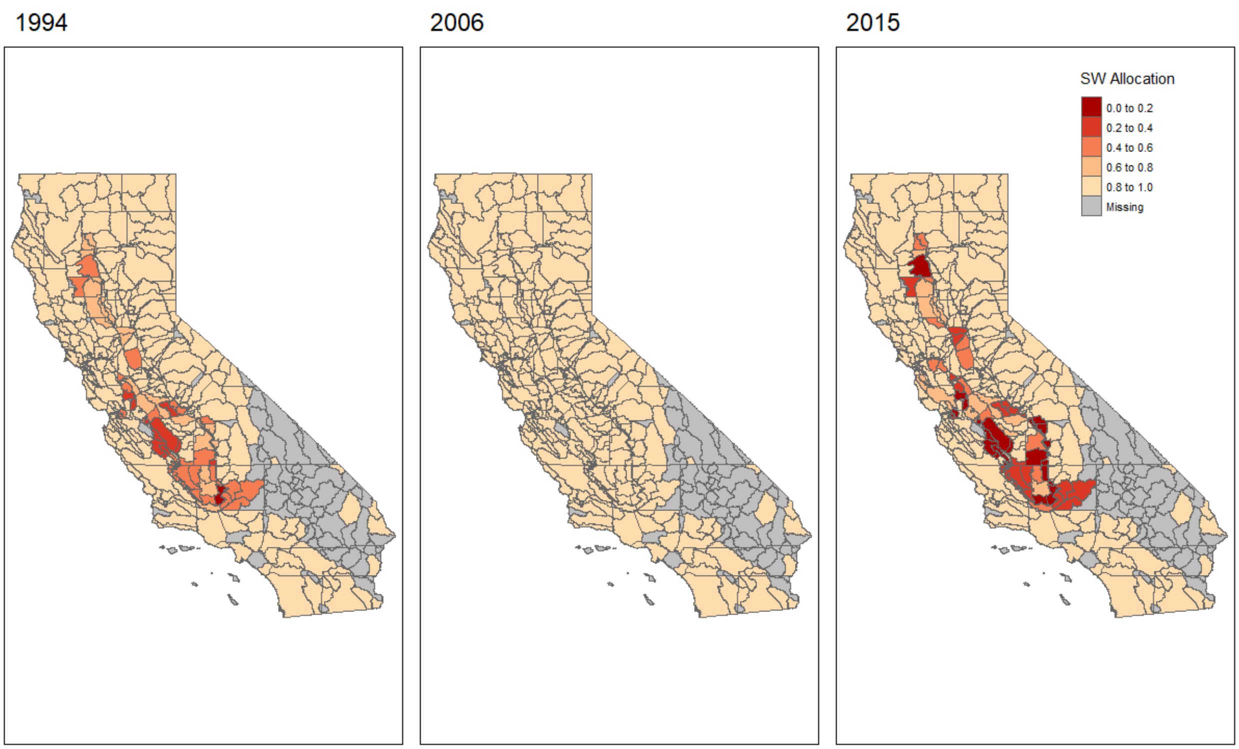
A primary outcome of interest is year-to-year changes in the depth to the water table from 20,000 monitoring wells between 1993 and 2020. Depth to the water table measures come from two sources: the State Water Resources Control Board (SWRCB) Groundwater Information System and DWR's Periodic Groundwater Level Measurement. [12] Within each monitor-year, we select a single date to measure the depth to the water table in a given year. We choose the reading closest to March 15 of the subsequent year (e.g. March 15, 2016 to measure the 2015 end of the year groundwater depth), since the water table will reflect the cumulative effects of groundwater pumping and recharge of the preceding year. These year-to-year differences measure the change in the depth to the water table.[13]

[11] There are a number of extreme values, likely due to measurement error. To account for this, we Winsorize this variable at 10 AF/acre.

[12] Figure A2 which plots the location of each unique monitoring well in our sample and the boundaries of California's principle groundwater basins. This figures highlights that there is broad coverage of monitoring wells in the agricultural centers of California, such as the San Joaquin Valley. While monitoring wells are more sparse in the Mojave Desert in Southeast California, this area contains very little agricultural land, and thus, is less relevant to this study.

[13] To account for outlier observations, we exclude observations that are more than 1.5 times the inner decile range of all other changes in groundwater levels reported from monitoring wells in the DAUCO over our sample. This rule removes observations with drastically different changes in groundwater levels than other local groundwater measures. Some of these outlier observations are the result of a misplaced decimal, while other errors could occur from monitor

Figure 2: Agricultural Surface Water Allocation Percentages



Note: The figure graphs the fraction of agricultural water entitlements to be received by irrigation districts at the DAUCO level for three years: 1994, 2006, and 2015. Allocation percentages, which are announced by the state prior to the growing season based on environmental conditions, vary over space and time.

As shown in Table 2, on average groundwater levels are declining by approximately 4 inches per year. However, this statistic masks substantial temporal and spatial heterogeneity in groundwater levels. Figure 3 illustrates the change in depth to the groundwater in each DAUCO in three different years. It makes clear that groundwater tables generally decline in drought years, and replenish during wet years. Declines are most pronounced in location-years that experience the largest surface water curtailments, with some regions experiencing annual declines of 10 feet.

Well Construction

We measure extensive-margin adaptation to surface water scarcity and extreme heat through the metric of new agricultural well construction. We use the universe of Well Completion Reports from DWR, which reports each well's location, the drilled depth of the well, intended use, and other characteristics.[14] Our final outcome is the count of the total number of new agricultural irrigation wells per DAUCO per year.

Figure 4 maps new agricultural well construction for the years 1994, 2006, and 2015. New well construction varies from year-to-year and increases during times of drought. This activity is also concentrated in the San Joaquin Valley. A visual comparison of Figures 2 and 4 suggests that well construction is more pronounced in location-years that experience the largest surface water curtailments.

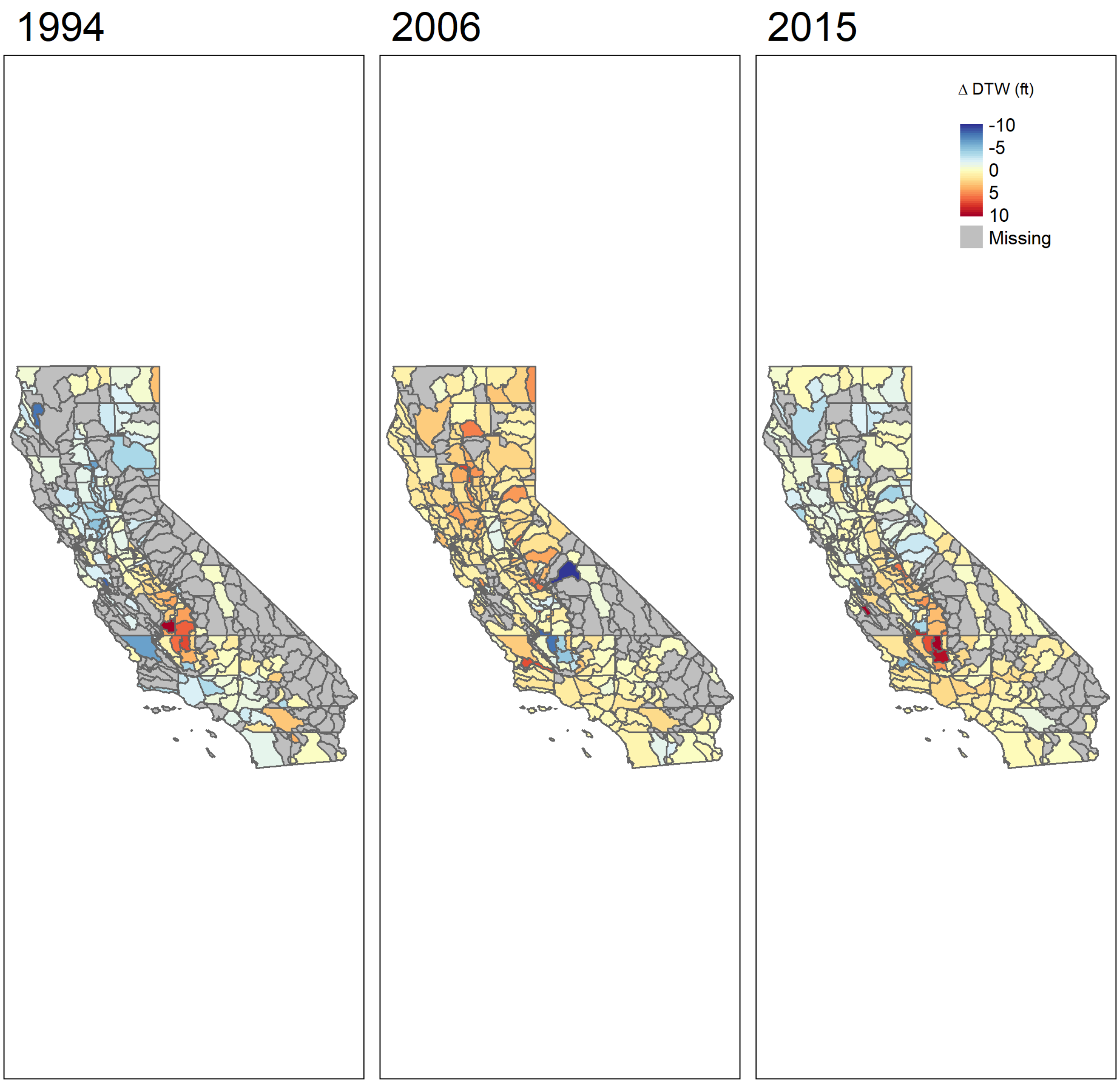
Well Failures

Panel data on domestic well failures at the well-year are available from 2014 to 2021. Beginning in 2014, DWR created a system for households to report domestic well failures. These data, shown on a map in Figure A3, contain the coordinates for the reported dry well, the date the issue started, and

errors. We cannot easily identify the source of measurement error in these data in order to assign accurate values, and therefore, remove these observations to reduce measurement error in our coefficient estimates.

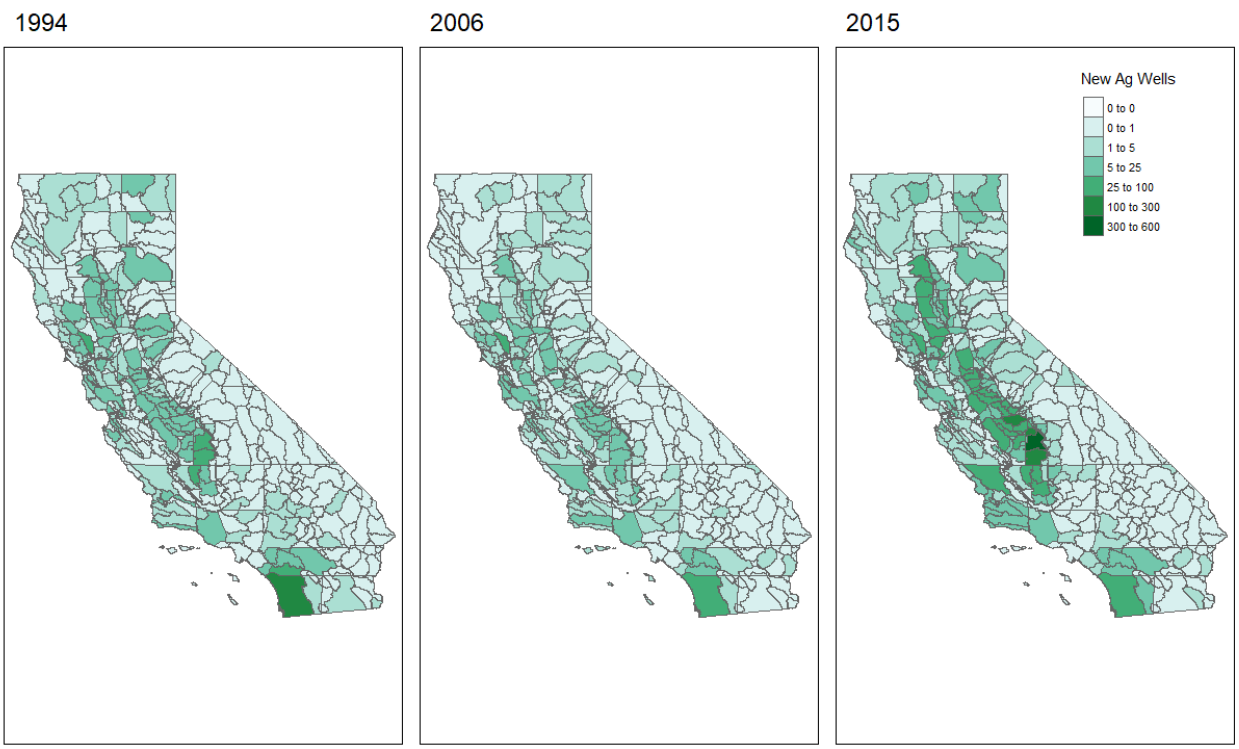
[14]Since 1949, the California Water Code requires that well owners complete a Well Completion Report with the California DWR within 60 days of the well construction. Prior to 2015, all Well Completion Reports were handwritten and later digitized for the construction of this dataset.

Figure 3: Annual Changes in Depth to the Water Table



NOTE: Figure displays the average changes in depth to the water table within a DAUCO for 1994, 2006, and 2015. During drought year, 1994 and 2015, areas in the San Joaquin Valley experience large reductions in groundwater depth. Whereas, in wet years, like 2006, those same areas experience small changes or even replenishment.

Figure 4: New Agricultural Well Construction



Note: The figure plots the count of new agricultural wells constructed at the DAUCO level for three snapshots in time: 1994, 2006, and 2015. New agricultural well drilling is predominant in the San Joaquin Valley.

if the issue was resolved. Using the Well Completion Report data, we create a panel of all domestic wells by geographically matching the reported failures to the registered domestic wells. We assign a well-year as failed if a well failure is self-reported; otherwise we assume it is functional. This is an undercount of the true number of domestic well failures, since household reporting is voluntary. Still it is an improvement on past approaches that estimate failures based on assumptions about the relationship between well depth and groundwater table height.

Since 2014, over 4,000 domestic well failures have been reported. The black outlined region of Figure A3 illustrates that these well failures are concentrated in California's San Joaquin Valley. They also occur disproportionately in locations that experience large agricultural surface water curtailments.

Weather

To measure extreme heat and precipitation we use weather observations from Schlenker and Roberts (2009) and PRISM climate data. We model temperature as harmful degree days (degree days over 32 degrees Celsius) and growing degree days (degree days over 8 and below 32 degrees Celsius). Precipitation is measured as local annual precipitation in millimeters. Schlenker and Roberts (2009) data, which are derived from PRISM weather station observations, end in 2019. We supplement weather observations using PRISM data for 2020 and 2021.

5 Empirical Model

Our empirical framework uses annual fluctuations in local weather and surface supplies to empirically quantify the theoretical channels through which these shocks can impose external costs. We first test the prediction that heat and surface water scarcity will lead to declining water availability as measured by changes in depth to the water table. We then evaluate the extent to which declining water tables impact drinking water access by testing the reduced form effects of surface water scarcity and heat on the probability of well failure. Lastly, we empirically isolate new agricultural well construction as one channel that explains declining water tables.

5.1 Estimation and Identification

Changes in Depth to the Water Table

To estimate the effect of heat and surface water scarcity on year-to-year changes in groundwater levels, we use annual panel data and begin by estimating a two-way fixed effects model using OLS,

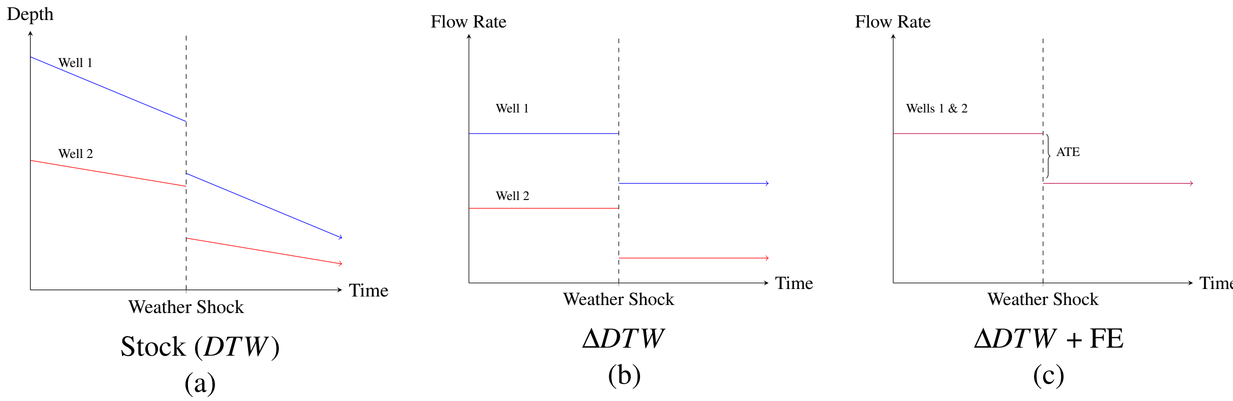
$$\Delta DTW_{idt} = \beta_1 SWD_{idt} + \beta_2 HDD_{idt} + B' X_{idt} + \lambda_t + \alpha_i + \varepsilon_{idt}. \tag{6}$$

The dependent variable, ΔDTW_{it}, is the year-to-year change in the depth to the water table for well i in year t. We have two primary regressors of interest: SWD_{idt} and HDD_{idt}. SWD_{idt} measures surface water deliveries in acre-feet per crop acre within the DAUCO region d where well i is located in year t. Similarly, HDD_{idt} is the annual number of harmful degree days within the monitoring well i's DAUCO d and year t. The vector X_{idt} captures other localized weather shocks, including precipitation and growing degree days. Fixed-effects λ_t capture statewide temporal shocks and trends, and α_i absorbs well-specific characteristics. Standard errors are clustered by DAUCO to account for serial correlation among wells within the same DAUCO.

The transformation, ΔDTW_{idt}, measures the *flow* of groundwater levels at well i, as opposed to the *stock* that is captured in the raw variable DTW_{it}.[15] Figure 5 illustrates this transformation within our context using two wells. First, panel (a) shows the raw groundwater stocks (DTW) over time for the two wells that start with different stocks and are depleted at different rates. Assume, for simplicity, that weather shocks only occur at a single point in time in this example, represented by the vertical dashed line. Panel (b) transforms the raw stock variable such that ΔDTW captures

[15] Hernandez-Cortes and Meng (2023) identify similar differential trends in their outcome measure of emissions. Our approach deviates from theirs, however, because they test for breaks in those trends by an individual policy, while we are interested in the impacts on flow rates from annual shocks.

Figure 5: Framework for Measuring Changes in Groundwater Stock with Differential Trends



Note: The figure shows a stylized illustration of two wells in two time periods. Panel (a) shows the depth to groundwater trajectory for two wells in the face of a weather shock. By taking the change in the depth to the water table in panel (b), we can measure the annual flow to the underlying stock. Panel (c) illustrates the average treatment effect (ATE) being measured with the inclusion of well fixed effects.

the different flow rates. The trends in flow rates are parallel across time. Finally, panel (c) shows that fixed effects will absorb the unique flow rates for each well, and we can capture the average treatment effect of weather shocks on changes in groundwater stock across wells.

The coefficient β_1, therefore, can be interpreted as the marginal effect of one AF/acre change in surface water on the change in groundwater levels, holding constant heat and other weather. β_2 is interpreted as the marginal change in depth to the groundwater resulting from an additional harmful degree day, holding constant surface water supplies. The regression is weighted by the inverse density of monitoring wells per DAUCO in order to obtain estimates that represent the effects for the average acre of cropland in California and correct for potential over-sampling from monitoring wells that may be geographically clustered.

As previously mentioned, surface water deliveries can potentially be manipulated by the users. In low surface water years, irrigation districts can influence their total delivery amount by purchasing water on the spot market or drawing from water banks. This behavior may be correlated with groundwater extraction and bias our estimates of equation 6. To account for this, we exploit

California's water allocation system as an instrument for surface water deliveries in a two-stage instrumental variables approach, following Hagerty (2021):

$$\begin{aligned} \Delta DTW_{idt} &= \beta_1 S\hat{W}D_{idt} + \beta_2 HDD_{idt} + B'X_{idt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\ SWD_{idt} &= \gamma_1 SDA_{idt} + \gamma_2 HDD_{idt} + \Gamma' X_{idt} + \lambda_t + \alpha_i + \mu_{idt}. \end{aligned} \tag{7}$$

All variables are defined as before but now we instrument for surface water deliveries with surface water allocations, SDA_{it}.

The use of allocations as an instrument in this setting hinges on the two standard instrumental variables assumptions. First, allocations must only affect the groundwater table through the margin of surface water that is delivered. Allocations are set ahead of the growing season based on that year's environmental conditions and are not used for any other regulatory decisions. Therefore, no obvious channel exists through which this assumption would be violated. Second, allocation must be a strong predictor of surface water deliveries. We present the F-statistic from the first stage in table A1, which exceeds conventional thresholds.

The primary identifying assumption for our general approach is that, conditional on well and year-fixed effects and local weather, allocation percentages and extreme heat are orthogonal to unobserved factors associated with groundwater stocks. Threats to this assumption stem from regional time-varying unobservables that correlate with both changes in water allocations and changes in the depth to the groundwater table. Our inclusion of local precipitation as a control is motivated by this concern. Insensitivity of the treatment effect to the inclusion and exclusion of time-varying local weather shocks included in X_{it} lends support for this identifying assumption.

Domestic Well Failures

Changes in the depth to the groundwater table may lead to domestic wells running dry. To estimate the effect of heat and surface water scarcity on domestic well failures, we use well-level panel data and again estimate an instrumental variable approach with two-way fixed effects using OLS,

$$
\begin{aligned}
Y_{idt} &= \beta_1 S\hat{W}D_{idt} + \beta_2 HDD_{idt} + B'X_{idt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\
SWD_{idt} &= \gamma_1 SDA_{idt} + +\gamma_2 HDD_{idt} + \Gamma' X_{idt} + \lambda_t + \alpha_i + \mu_{idt}
\end{aligned}
\tag{8}
$$

Here, Y_{idt} is a binary outcome indicating whether domestic well i reported running dry in year t. The right-hand side variables are defined the same as equation 7. Domestic well fixed effects, α_i, control for time-invariant characteristics of the well, like location and depth of the well. The coefficient estimates of interest from this equation, β_1 and β_2, represent the change in likelihood that a domestic well fails in a given year resulting from changes in surface water availability and extreme heat, respectively. The regressions are weighted by the number of crop acres in the DAUCO. Standard errors are clustered at the DAUCO level.

Identification of β_1 and β_2 as the causal impacts of surface water scarcity and heat on the likelihood of domestic well failure rests on a similar set of three assumptions. Regional time-varying factors that correlate with both domestic well failures and surface water allocations remain a threat to identification. To alleviate this concern, we again control for local weather shocks in X_{idt}. The other identifying assumptions concern the instrument for surface water deliveries. Like before, we assume allocations affect domestic well failures only through the margin of surface water deliveries and that allocations are a strong predictor of surface water deliveries.

Agricultural Well Construction

Our final outcome of interest is new agricultural well construction. We focus on well construction because it is the one observable mechanism that contributes to the reduction in groundwater tables. New agricultural wells represent the observable extensive-margin response that complements the unobservable intensive-margin response of increased pumping. To estimate the effects of drought and surface water curtailment on agricultural well construction, we construct a balanced panel on agricultural well construction, surface water, and weather at the Detailed Analysis Unit by County (DAUCO) and annual level.

In this regression, our outcome of interest is the non-negative count of new agricultural wells and may suffer from over-dispersion. For this reason, we deploy a control function approach with fixed effects estimated with Psuedo-Poisson Maximum Likelihood (PPML) (Wooldridge, 2015), shown in equation 9. For robustness, we also report the result from the linear two-stage least squares, similar to the previous outcomes.

$$\begin{gathered}E[Y_{dt}|SWD_{dt}, HDD_{dt}, \mathbf{X}_{dt}, \alpha_d, \lambda_t] = \exp\{\beta_1 S\hat{W}D_{dt} + \beta_2 HDD_{dt} + B'X_{dt} + \alpha_d + \lambda_t + \phi\hat{\mu}_{dt}\} \\ SWD_{dt} = \gamma_1 SDA_{dt} + \gamma_2 HDD_{dt} + \Gamma' X_{dt} + \alpha_d + \lambda_t + \mu_{dt}.\end{gathered} \tag{9}$$

All variables are defined as before except now the variable Y_{dt} measures the count of new agricultural wells where d signifies the DAUCO and t denotes the year between 1993 and 2020. The variable α_d represents DAUCO fixed effects that account for the fact that DAUCO's may have different base-rates of well drilling and other time-invariant characteristics that are associated with well construction. Time-fixed effects, γ_t, control for annual shocks, like recession, that may impact statewide well drilling rates.

The coefficient β_1 indicates that for every one AF/acre decrease in surface water deliveries, the number of new agricultural wells will change by $e^{\beta_1} - 1$ percent. Similarly, for every additional harmful degree day, $e^{\beta_1} - 1$ percent more agricultural wells will be constructed. This method also allows us to test for endogeneity of surface water deliveries by including $\hat{\mu}_{dt}$ in the second stage. The strength and significance of engodentiy is captured by ϕ. All regressions are weighted by crop acres, which identifies the average treatment effect across California crop acres. Standard errors are clustered at the DAUCO level.

6 Results

Results from the estimation of equation 7 are reported in Table 3. Columns (1) and (2) report results from the reduced-form effect of per-acre allocations on the change in groundwater depth with and without controls for local weather. Columns (3) and (4) present IV results where allocations are used as an instrument for surface water deliveries. In our preferred specification in column (4), we condition on local weather variables: Annual precipitation and growing degree days.

The reduced-form results, which represent an estimate of the intent to treat, show that surface water allocations have a negative and significant impact on changes in the depth to the water table. The table shows that allocations are relevant to agricultural groundwater pumping and affect the underlying groundwater table through changes in surface water deliveries. However, reduced-form results are attenuated because allocations are not perfectly correlated with surface water deliveries.

A first central result is that extreme heat and surface water scarcity lower the groundwater table and lead to groundwater depletion. Our preferred estimates in column (4) of Table 3 imply that a one AF/acre reduction in SW deliveries leads to a 2.9 ft decline in the groundwater levels, extreme heat held constant. We also see that groundwater depth is also responsive to extreme heat, with groundwater levels declining by 0.03 ft for every additional harmful degree day. To contextualize these results, 2021 was both a statistically dry and hot year, where California crop acres received 1.53 AF/acre of surface water (0.7 AF/acre below average) and 120 HDD (23 HDD above average).[16] Therefore, surface water curtailments equal to 2021 levels resulted in a 2 ft decline across California. These results also imply that 2021 levels of extreme heat, holding constant surface water supplies, caused a 0.7 ft decline in groundwater levels.

This extraction of the groundwater stock, which manifests through changes in the depth to the water table, generates externalities for other users of the resource.[17] In this context, the external costs imposed by groundwater pumpers who are reacting to changes in heat and surface

[16]For more of a historical context on the size of typical shocks, we can reference the sample "within" standard deviation by calculating the standard deviation of surface water and heat for each DAUCO across time, and compute the average across all DAUCOs. A one "within" standard deviation change is equal to 0.54 AF/acre for surface water and 14 HDD for extreme heat.

[17]However, it should be noted that the depletion in groundwater stock also represents private pumping costs and costs of future scarcity that are conceivably internalized by the producer.

Table 3: Changes in Depth to the Groundwater (DTW)

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-1.967**	-1.533*		
	(0.674)	(0.636)		
Ag SW Deliveries (AF/acre)			-3.684**	-2.914*
			(1.196)	(1.174)
Harmful Degree Days		0.0308		0.0309**
		(0.0160)		(0.0115)
Observations	561085	560931	561085	560931
N Groups	83782	83762	83782	83762
Weights	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. Columns (1) and (2) report results from the reduced-form OLS model. Columns (3) and (4) report the second-stage IV results, where Ag surface water allocations are used as an instrument. All regressions are weighted by the DAUCO crop acres divided by the number of monitoring wells and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

water scarcity are borne by neighboring users and future users of the groundwater. This externality disproportionately puts household users of groundwater at risk since domestic wells are generally drilled shallower on average and are more susceptible to well failure.

To explore this, we estimate a panel linear probability model of the probability of domestic well failure on heat and surface water scarcity. Table 4 displays the results from the estimation of equation 8. Column (1) presents the reduced-form effect of per-acre allocations and heat on probability of a well failure with time and well fixed effects using data from 2015 to 2020. Column (2) conditions on local weather. Columns (3) and (4) report the results from the instrumental variable model. Our results demonstrate that extreme heat and surface water scarcity compromise access to drinking water through the channel of well failures. Our preferred specification in column

Table 4: Linear Probability of Reported Well Failure

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-0.0156*	-0.0280		
	(0.00705)	(0.0156)		
Ag SW Deliveries (AF/acre)			-0.0296**	-0.0557**
			(0.00986)	(0.0192)
Harmful Degree Days		0.00212*		0.00208*
		(0.000950)		(0.000908)
Observations	468,333	468,075	468,313	468,055
N Groups	78,084	78,041	78,064	78,021
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(4) implies that an additional harmful degree day increases the probability that a well fails by 0.2%. That specification also displays that a one AF/acre reduction in surface water increases the likelihood of local domestic well failure by 5%. These estimates imply that for 2021 levels of weather shocks, well failure probability increases by 3.4% as a result of surface water curtailments, and 4.8% due to extreme heat. These estimates are large marginal effects relative to the sample mean probability of well failure displayed in Table 2.

Table 5 shows that well failures resulting from weather shocks are concentrated in low-income populations and among people of color. To test for distributional impacts, we decompose the overall treatment effect by subgroup by interacting an indicator for well failure and an indicator for each subgroup. Columns (2) and (3) decompose the effect among low and high-income census tracts. Similarly, columns (4) and (5) separate the treatment effect into census tracts that have above

Table 5: Probability of Domestic Well Failure: By Demographics

	Pooled	Income		Race	
	(1)	(2)	(3)	(4)	(5)
		Low	High	Nonwhite	White
Ag SW Deliveries (AF/acre)	-0.0557**	-0.0554**	-0.000269	-0.0559**	0.000188
	(0.0192)	(0.0192)	(0.00101)	(0.0192)	(0.000127)
Harmful Degree Days	0.00208*	0.00206*	0.0000133	0.00208*	-0.00000687
	(0.000908)	(0.000905)	(0.0000224)	(0.000908)	(0.00000858)
Observations	468067	468067	468067	468067	468067
N Groups	78025	78025	78025	78025	78025
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓	✓
Other Weather	✓	✓	✓	✓	✓

Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. For columns 2-4, the well failures are partitioned by whether they occur in a census tract above/below median poverty rates and above/below median percent nonwhite population. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and below the median percent nonwhite populations, respectively. Both sets of results show that over 99% of the treatment effects of surface water deliveries and HDD occur in low-income and nonwhite populations, while higher-income and whiter populations exhibit negligible impacts. Our results highlight that in California low-socioeconomic communities bear the burden of climate-driven changes in groundwater levels from agricultural extraction.

Our final set of results explores one mechanism by which agricultural groundwater users can respond to heat and surface water scarcity: the construction of new wells. Table 6 reports the estimates of new agricultural well construction on surface water deliveries, where surface water deliveries are instrumented by allocations. Columns (1) and (2) report the result from a linear IV specification. Columns (3) and (4) are estimated using a control function approach with a linear first stage and PPML in the second stage. Controls for extreme heat and other weather are included in columns (2) and (4). This table makes clear that heat and surface water scarcity induce farmers to construct more agricultural wells. Our estimates imply that farmers drill approximately 46.2%

Table 6: Construction of New Agricultural Wells: IV and Control Function

	IV		CF/PPML	
	(1)	(2)	(3)	(4)
Ag SW Deliveries (AF/acre)	-13.06**	-12.38**	-0.690**	-0.620*
	(4.584)	(4.750)	(0.262)	(0.262)
Harmful Degree Days		0.111***		0.0128***
		(0.0329)		(0.00261)
$\hat{\mu}$			0.732*	0.767*
			(0.346)	(0.347)
Observations	9,660	9,240	8,568	8,400
N Groups	345	330	306	300
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses. Columns (3) and (4) standard errors are calculated using 500 bootstrap simulations, clustered at the DAUCO level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

more agricultural wells for an AF/acre reduction in surface water and 1.3% more for every HDD increase.[18] Using surface water shocks and extreme heat experienced in 2021, our results imply that farmers spent $24 million to construct 321 more wells that were drilled because of surface water curtailments and $22 million to construct 294 as the result of extreme heat.[19]

In addition to drilling more wells, it could be the case that farmers are responding by drilling deeper wells. Table A8 in the Appendix considers the effect of surface water and temperature shocks on the drilled depth of newly constructed wells, both agricultural and domestic. Results suggest some evidence of this although estimates are imprecise.

[18] Recall estimates must be transformed by $e^{\beta} - 1$ in order to be interpreted as a percent change for Poisson models.

[19] This back-of-the-envelope calculation uses values from the California Assessors Handbook on average well-drilling costs and average agricultural well characteristics from the Well Completion Reports (California State Board of Equalization, 2023).

One concern is that weather shocks simply induce a shift in the timing of well construction as opposed to a marginal increase in total wells. A concern with this kind of inter-temporal substitution is that this specification, which focuses only on the contemporaneous effect, would be overestimating the treatment effect. Tables A4 and A5 in the Appendix consider the dynamics of agricultural well drilling by including lagged surface water deliveries and harmful degree days. We find that the impacts of weather shocks have a significant impact on contemporaneous well construction, even when lagged surface water and heat are included in the regressions. Furthermore, we do not find consistent evidence of inter-temporal substitution among any of the alternative specifications. We discuss the findings of the dynamic regressions in more detail in section A.2.

Extensive and Intensive Margin Adaptation

Based on the model set forth in equation 3, we use the point estimates on change in groundwater depth and new well construction to back out the intensive margin response to heat and surface water scarcity. This exercise relates changes in groundwater levels (i.e., changes in water-occupied space) within an aquifer (DTW) to behavioral changes in the volume of groundwater pumped for agricultural use. To do this, we need to introduce values for three parameters from our conceptual framework as described in equation 3. We assign these values based on our raw data and the literature relevant to the Central Valley of California as described in Table A3. Together, these values allow us to decompose the change in groundwater depth into the intensive and extensive margin response.

We report the calculations from this exercise on an AF/acre basis such that they are consistent units as our primary measure of surface water in our empirical models. A one AF/acre reduction in surface water results in a 2.91 ft ($\frac{dDTW}{ds}(s,h)$) decline in groundwater levels, or equivalently, 0.40 AF/acre additional gross groundwater extraction ($\frac{dDTW}{ds}(s,h) \times \frac{1}{\kappa}$). Given our estimates of new agricultural wells drilled in Table 6, we calculate that approximately 0.01 AF/acre of that effect results from new wells, or 81,750 AF statewide. While 0.39 AF/acre of the gross effect is due to the intensification of existing wells, or 4,410,000 AF statewide.

Extensive margin adaptation by farmers accounts for about 2.3% (6.2%) of the effect on groundwater levels results from surface water curtailments (harmful degree days), while the majority of the gross effect results from intensifying the average amount of water pumped per well. The large difference between extensive and intensive margins is likely due to the high fixed costs associated with drilling new agricultural wells. New agricultural wells, however, likely increases the groundwater demand in years beyond just the contemporaneous year. Whereas, intensive margin adjustments are isolated decisions in the contemporaneous year. Over the life of a groundwater well, the cumulative extensive margin effect may outweigh large single-year, intensive margin adjustments.

Understanding these mechanisms through which agricultural producers respond to weather shocks and the subsequent impacts can better inform policy aimed at conserving water resources. We show that farmers substitute at least 40% of the lost surface water with groundwater supplies when surface water curtailments are imposed. This helps mitigate the yield effects of the weather shocks, but strains historically unregulated groundwater resources. We also show that farmers adapt through both the extensive and intensive margin to these shocks, implying that groundwater regulation must target both mechanisms of behavior – reducing excess pumping at the well-level and restricting the drilling of new wells–in order to be effective.

7 Discussion

The impacts of climate change depend on the extent to which individuals adapt. While climate adaptation by some may limit their own potential damages from extreme heat and precipitation variability, these adaptive measures may unintentionally impose costs on others. In this paper, we show that agricultural producers in California significantly adapt to added heat and reduced surface water through the channel of constructing new agricultural wells. We also show that local groundwater levels are responsive to these annual fluctuations in weather. These climate-induced changes deplete local groundwater resources, imposing externalities on other users of groundwater. Negative externalities arise for rural communities through the channel of domestic well failures and subsequent reductions in drinking water access.

These findings contribute to the knowledge of the impact of climate change in three ways. First, we show that producers in California spend approximately $24 million annually for every AF/acre reduction of surface water availability and $22 million to mitigate the damages of heat. While irrigation may mitigate agricultural yield and revenue damages, climate change still imposes a significant annual cost to irrigated agriculture. Second, adaptation strategies contribute additional burden on those less able to engage in adaptive behavior. These externalities of adaptation have traditionally been ignored in calculating the economic costs of climate change but should be taken into account for a more complete accounting of climate change damages. Importantly, these externalities are borne in low socioeconomic communities, increasing environmental inequality. Results are relevant for policymakers seeking to implement environmental regulation.

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Appendix

A.1 Supplementary Tables and Figures

Table A1: Agricultural SW Deliveries: First-Stage Results

	(1)	(2)
Ag SW Allocation (AF/ acre)	0.588***	0.531***
	(0.0460)	(0.0540)
Harmful Degree Days		-0.000353
		(0.00172)
Growing Degree Days		0.000184***
		(0.0000432)
Annual Precipitation		-0.000461*
		(0.000202)
Observations	9,660	9,240
N Cluster	345	330
F Stat	163.6	79.07
Weights	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO
Time FE	✓	✓
Unit FE	✓	✓

Note: The table presents the first-stage effect of surface water allocations on surface water supplies. The dependent variable is agricultural surface water deliveries per crop acre in levels from 1993-2021. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Construction of New Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-7.180**	-6.581*	-0.333*	-0.278*
	(2.665)	(2.596)	(0.131)	(0.124)
Harmful Degree Days		0.115**		0.00897***
		(0.0390)		(0.00202)
Observations	9,660	9,240	8,568	8,400
N Cluster	345	330	306	300
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

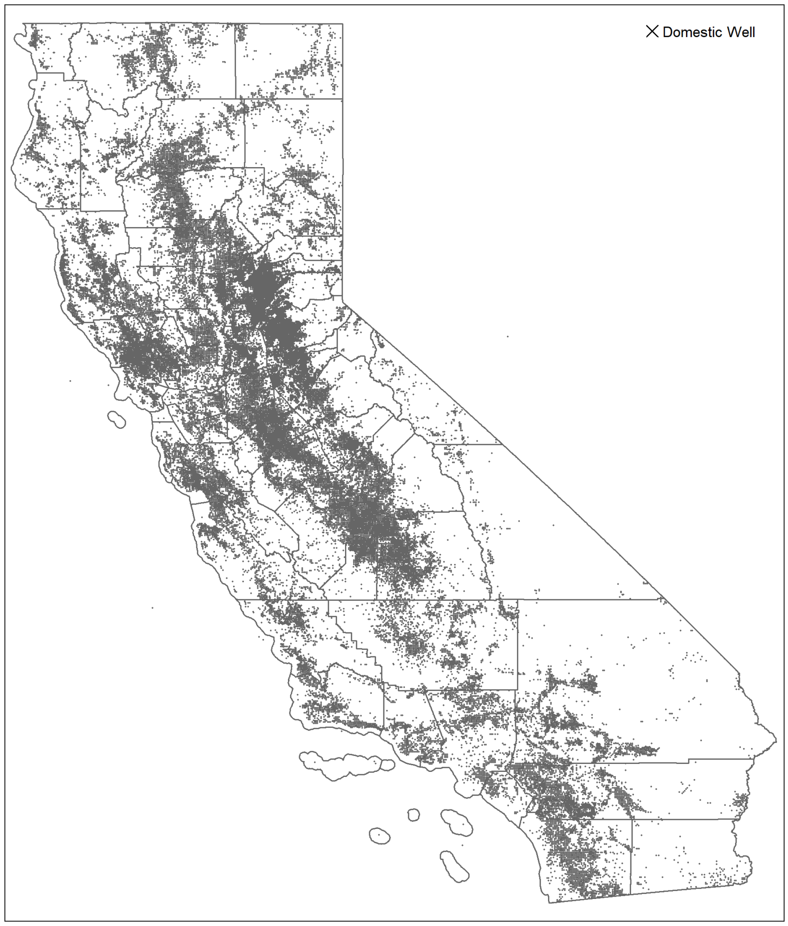
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Parameter Values for Decomposition

Parameter	Value	Units	Description	Source
$\frac{dDTW}{ds}(s,h)$	-2.91	ft	Gross change in DTW caused by a one AF/acre change in surface water	Table 3 Column 4
$\frac{dDTW}{dh}(s,h)$	0.031	ft	Gross change in DTW caused by one additional HDD	Table 3 Column 4
κ	8.33	unitless	Inverse aquifer yield coefficient	Department of Water Resources (2020)
$\frac{\partial w}{\partial s}$	-459	# of wells	Change in the number of new agricultural wells drilled due to a one AF/acre change in surface water	Table 6 Column 4 multiplied by the total annual average of new agricultural wells
$\frac{\partial w}{\partial h}$	12.8	# of wells	Change in the average number of new agricultural wells drilled due to one additional HDD	Table 6 Column 4 multiplied by the total annual average of new agricultural wells
q	178	AF/well	Average AF of groundwater pumped per well	Authors' calculation from Department of Water Resources (2020) and w
w	85,937	# of wells	Number of wells drilled in California	Well Completion Reports (see Data)
acres	9,989,648	# of acres	Total irrigated crop acres in California	2015 USDA Cropland Data Layer & Hagerty (2021)

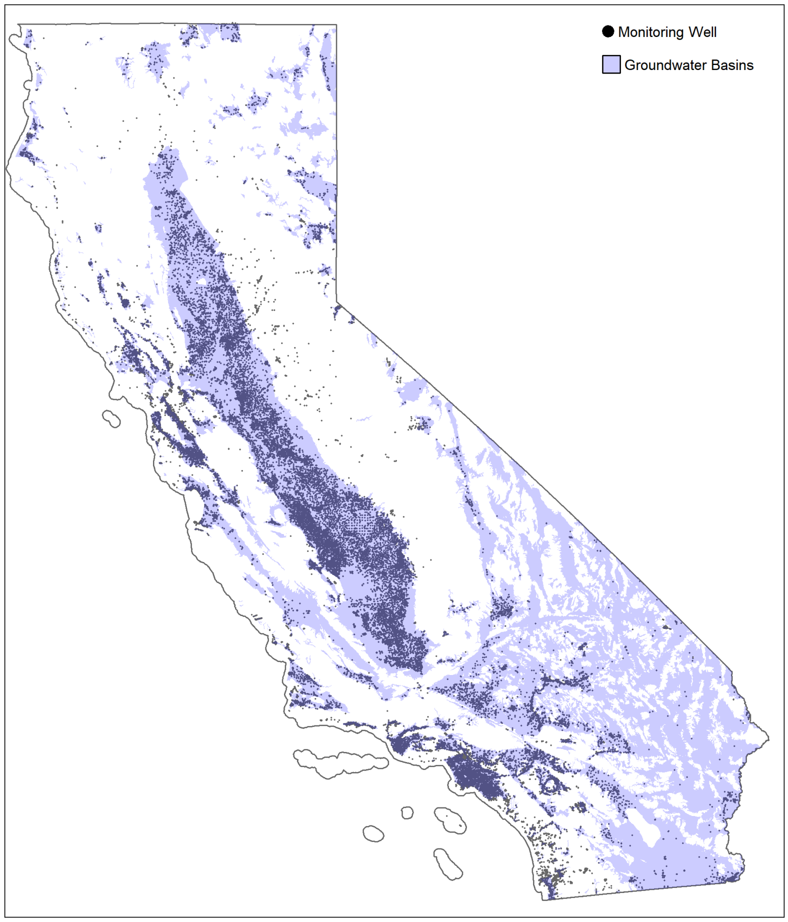
Note: The table reports estimated and calculated values for parameters in the decomposition of intensive and extensive margin effects presented in equation 3.

Figure A1: Location of Domestic Wells



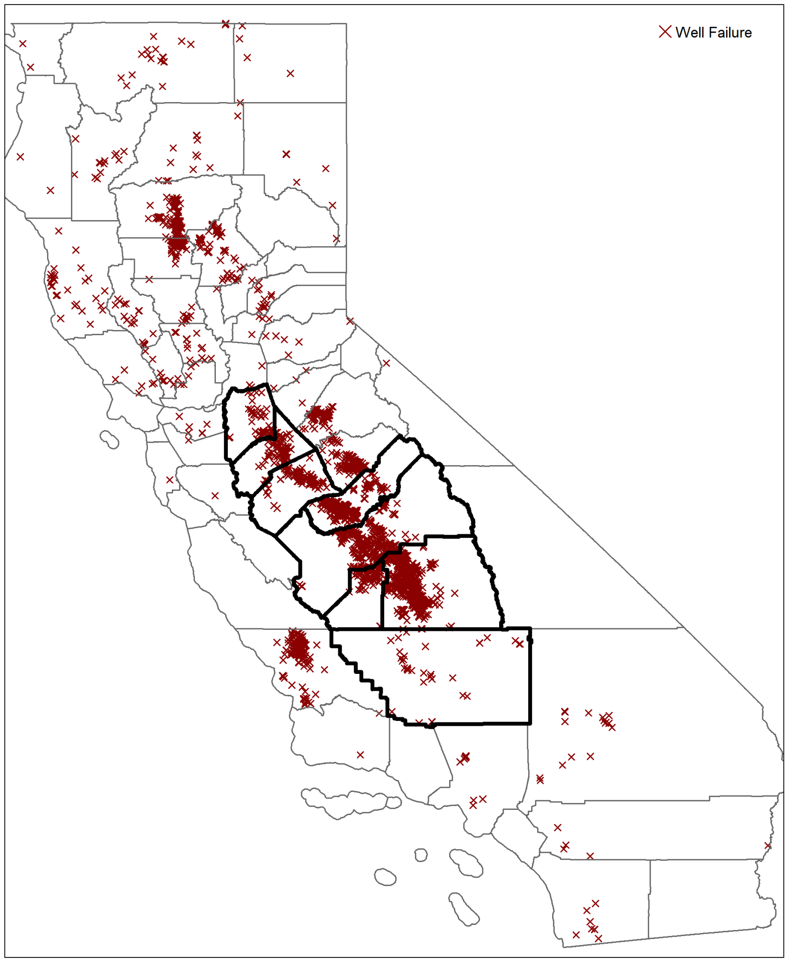
Note: The figure shows a location domestic groundwater wells constructed. Data are from Well Completion Reports from DWR.

Figure A2: Location of Monitoring Wells in California Groundwater Basins



NOTE: Figure displays the locations of groundwater monitoring wells and California's principle groundwater basins. Each dot displays a unique groundwater monitoring well reported in our dataset. The blue shaded areas display the locations of Bulletin 118 groundwater basins in California.

Figure A3: Locations of Reported Well Failures, 2014-2020



Note: This figure plots the locations of all reported well failures from 2014-2020 from the Dry Wells Reporting System from California DWR. Counties in the San Joaquin Valley have a thick border, and a large share of reported well failures occur in these counties.

A.2 Additional Empirical Specifications

Tables A4 and A5 consider the dynamics of agricultural well drilling. In Table A4, we report the results a linear IV for well construction, similar to columns (1) and (2) of table 6 but now supplemented with up to three lagged years of agricultural surface water deliveries. Columns (2) through (4) each add an additional lag. In these specifications, deliveries are instrumented with surface water allocations. Table A5 similarly considers the dynamic effects on new agricultural well construction but instead focuses on the reduced-form effect of surface water allocations with the Poisson transformation. This is because the control function approach outlined in equation 9 is incompatible with lagged variables that enter nonlinearly. A look at the coefficients on lagged surface water supplies across all specifications reveals no consistent pattern. The sum of the coefficients, which captures the effect of a single supply shock over time, are not statistically different from each other across specifications. This suggests that the contemporaneous effect is characterizing the most meaningful impact of year-to-year changes in water supplies on new agricultural well construction.

These results can be explained by the presence of two opposing forces at play. On the one hand, heat and surface water shocks may alter farmers' expectations about future climate conditions and water availability, causing them to drill more wells today and over the lifetime of their operations. Realizations of drought increase the incentive to drill by increasing the cost of delaying.

On the other hand, it may be the case that farmers are simply shifting forward in time the decision to drill a new well. A behavioral response that only consists of inter-temporal substitution would suggest that coefficients on lagged variables should take the opposite sign of the contemporaneous effect, because drilling a well today reduces the need to drill in the future. This in turn would cause the sum of the coefficients to attenuate as we add more lagged variables. Since we see no observable trend from the inclusion of the lagged variables, it suggests that neither of these forces are dominating. These two effects are working in opposite directions and cannot be teased out. Taken together, this pattern of results on lagged variables support our main results reported in Table A2. The vast majority of the effects of drought on well construction are concentrated in the first year. We proceed by focusing on the more parsimonious specification of equation 9 and retaining power with more observations.

The effects of surface water reductions and heat could conceivably impact groundwater outcomes in future years as well. If more agricultural wells are drilled in the contemporaneous year, this extensive margin change may also result in additional groundwater extraction – and thus, a lower groundwater table – in future years as well. If dynamics are present, it may imply that the contemporaneous effect alone is a lower bound of the cumulative effect of surface water and heat shocks. Table A6 reports estimates of changes in groundwater depth (ΔDTW) regressed on lagged weather shocks.

In general, there appears to be no significant nor consistent pattern among the coefficients from previous years. On the one hand, the coefficients on previous year's surface water deliveries tend to be positive, meaning they somewhat offset the contemporaneous effect. On the other hand, the previous year's HDDs report a positive coefficient, meaning that the current year's heat alone underestimates the true impact. However, the standard errors on the lagged effects tend to be large, and therefore, we conclude that the effects of weather shocks on changes in groundwater depth tend to be isolated to the contemporaneous year.

Similarly, we explore the impacts of prior weather shocks on reported well failures in Table A7. Columns (2) and (3) indicate that the effects of a one AF/acre surface water reduction may result in as much as a 32% increase in the probability of well. However, this is the opposite direction of the lagged effects of harmful degree days. We are hesitant to draw definitive conclusions from this table, however, since the panel only consists of five total years of well failure data.

In addition to drilling more wells, it could be the case that farmers are responding by drilling deeper wells. Table A8 considers the effect of drought on the drilled depth of newly constructed wells, both agricultural and domestic. Columns (1) to (3) present results of the effect of surface water allocations and harmful degree days on well depth, conditional on time and unit fixed effects and weather variables. Columns (2) and (3) isolate agricultural and domestic wells, respectively. Columns (4) through (5) present the IV results where allocations are used as an instrument for deliveries. While noisy, the sign of the effects suggest that as surface water supplies decrease and heat increases, wells are drilled to a greater depth.

Lastly, we conduct two falsification tests of our primary model. First, Table A9 reports the results of regression new domestic well construction on agricultural surface water deliveries and harmful degree days. Since agricultural surface water allocations are solely related to the agricultural sector, we expect shocks to this variable to be unrelated to domestic well construction. Indeed, none of the coefficients report a significant effect on the new domestic well construction. Furthermore, additional HDDs do induce more domestic wells to be drilled, but the response is smaller in magnitude than for agricultural well construction. This supports that agricultural well drilling is due to reduced surface water for agriculture, and not some correlated factor with all types of well drilling more broadly. Further, this also shows that domestic households are unable to respond to heat to the same degree as agricultural groundwater users, and thus, more vulnerable to groundwater scarcity in the future.

We explore whether shocks in surface water supplies to other sectors, municipal and industrial, impact agricultural well drilling in table A10. These results indicate that municipal and industrial water supplies are actually positively correlated with agricultural well construction, which is opposite of the effect of agricultural surface water. None of these coefficients are significant, and again, supports that the results in Tables A2 and 6 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

Table A4: Lagged Agricultural Well Construction

	(1)	(2)	(3)	(4)
	New Ag Wells per DAUCO			
Ag SW Deliveries (AF/ crop acre)	-12.38**	-11.51**	-11.53*	-11.45*
	(4.750)	(4.450)	(4.582)	(4.537)
L.Ag SW Deliveries (AF/ crop acre)		-3.512	-2.999	-3.602
		(2.858)	(2.779)	(3.207)
L2.Ag SW Deliveries (AF/ crop acre)			1.377	3.089
			(2.355)	(2.505)
L3.Ag SW Deliveries (AF/ crop acre)				-4.109
				(2.853)
$\sum \beta_{delieveries}$	-12.38	-15.02	-13.15	-16.07
$p_{deliveries}$	0.00913	0.00877	0.0277	0.0355
Harmful Degree Days	0.111***	0.0981**	0.0971**	0.0897**
	(0.0329)	(0.0349)	(0.0318)	(0.0327)
L.Harmful Degree Days		0.0809*	0.0848*	0.0548
		(0.0397)	(0.0426)	(0.0390)
L2.Harmful Degree Days			0.0551*	0.0643**
			(0.0247)	(0.0239)
L3.Harmful Degree Days				0.0174
				(0.0237)
$\sum \beta_{hdd}$	0.111	0.179	0.237	0.226
p_{hdd}	0.000760	0.00484	0.00171	0.00302
Observations	9,240	8,910	8,580	8,250
N Cluster	330	330	330	330
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Other Weather	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Table reports regression results from a lagged linear IV model. The dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Lagged Agricultural Well Construction

	(1)	(2)	(3)	(4)
	New Ag Wells per DAUCO			
Ag SW Allocation (AF/crop acre)	-0.278*	-0.284*	-0.306*	-0.281*
	(0.124)	(0.130)	(0.126)	(0.137)
L.Ag SW Allocation (AF/crop acre)		0.0184	-0.0150	-0.0370
		(0.0500)	(0.0436)	(0.0495)
L2.Ag SW Allocation (AF/crop acre)			0.157	0.184*
			(0.0835)	(0.0814)
L3.Ag SW Allocation (AF/crop acre)				-0.0202
				(0.0715)
$\sum \beta_{deliveries}$	-0.278	-0.266	-0.164	-0.154
$p_{deliveries}$	0.0249	0.0481	0.235	0.338
Harmful Degree Days	0.00897***	0.00958***	0.00915**	0.00972**
	(0.00202)	(0.00261)	(0.00287)	(0.00323)
L.Harmful Degree Days		0.00331	0.00435	0.00190
		(0.00266)	(0.00250)	(0.00251)
L2.Harmful Degree Days			0.00447	0.00383
			(0.00254)	(0.00266)
L3.Harmful Degree Days				0.00521*
				(0.00240)
$\sum \beta_{hdd}$	0.00897	0.0129	0.0180	0.0207
p_{hdd}	0.00000911	0.000326	0.000125	0.000110
Observations	8,400	8,073	7,722	7,400
N Cluster	300	299	297	296
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Lagged Changes in Groundwater Depth

	(1)	(2)	(3)	(4)
		ΔDTW		
Ag SW Deliveries (AF/ crop acre)	-3.754*	-3.807*	-4.785**	-4.650**
	(1.619)	(1.525)	(1.580)	(1.743)
L.Ag SW Deliveries (AF/ crop acre)		1.668	1.456	1.569
		(1.009)	(0.958)	(0.900)
L2.Ag SW Deliveries (AF/ crop acre)			0.141	-0.265
			(0.999)	(1.030)
L3.Ag SW Deliveries (AF/ crop acre)				-0.233
				(0.464)
$\sum \beta_{deliveries}$	-3.754	-2.139	-3.187	-3.579
$p_{deliveries}$	0.0204	0.118	0.0205	0.0346
Harmful Degree Days	0.0373*	0.0376*	0.0388*	0.0345*
	(0.0169)	(0.0168)	(0.0162)	(0.0152)
L.Harmful Degree Days		0.0109	0.0215	0.0301*
		(0.0106)	(0.0112)	(0.0146)
L2.Harmful Degree Days			-0.0129	-0.0230
			(0.0131)	(0.0131)
L3.Harmful Degree Days				-0.00683
				(0.0290)
$\sum \beta_{hdd}$	0.0373	0.0486	0.0474	0.0348
p_{hdd}	0.0273	0.0152	0.0279	0.214
Observations	560,931	421,251	321,384	246,159
N Cluster	282	277	269	260
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Lagged Probability of Well Failure

	(1)	(2)	(3)	(4)
	Well Failure Reported			
Ag SW Deliveries (AF/ crop acre)	-0.0548**	-0.0397**	-0.178**	0.000778
	(0.0191)	(0.0131)	(0.0597)	(0.0277)
L.Ag SW Deliveries (AF/ crop acre)		-0.0677*	-0.177*	-0.0296
		(0.0265)	(0.0691)	(0.0278)
L2.Ag SW Deliveries (AF/ crop acre)			0.0257	-0.0216
			(0.0168)	(0.0122)
L3.Ag SW Deliveries (AF/ crop acre)				0.00908
				(0.00649)
$\sum \beta\_deliveries$	-0.0548	-0.107	-0.329	-0.0414
$p_{deliveries}$	0.00415	0.000413	0.00529	0.453
Harmful Degree Days	0.00205*	0.00157*	0.00142*	0.0000432
	(0.000899)	(0.000759)	(0.000634)	(0.0000781)
L.Harmful Degree Days		-0.00333*	-0.00187	0.000179
		(0.00166)	(0.00116)	(0.000168)
L2.Harmful Degree Days			-0.000906	-0.000166
			(0.000612)	(0.000161)
L3.Harmful Degree Days				0.0000875
				(0.000150)
$\sum \beta_{hdd}$	0.00205	-0.00176	-0.00135	0.000144
p_{hdd}	0.0228	0.106	0.364	0.745
Observations	476,748	476,748	397,290	317,832
N Cluster	342	342	342	342
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: New Constructed Well Depth

	Reduced Form			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Both	Ag	Domestic	Both	Ag	Domestic
Ag SW Allocation (AF/ crop acre)	-22.90	-23.14	-8.170			
	(18.16)	(21.67)	(7.699)			
Ag SW Deliveries (AF/ crop acre)				-37.03	-34.48	-14.14
				(29.10)	(32.23)	(14.34)
Harmful Degree Days	1.431*	2.592*	0.346	1.340*	2.449*	0.319
	(0.624)	(1.108)	(0.244)	(0.563)	(1.019)	(0.237)
Observations	144,917	31,042	114,034	144,890	30,955	113,863
N Groups	337	310	334	328	295	322
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓	✓	✓
DAUCO x Type FE	✓	✓	✓	✓	✓	✓
Other Weather	✓	✓	✓	✓	✓	✓

Note: Dependent variable is the depth (ft) of newly constructed wells from 1993-2020 at the well level. Columns (1) and (4) reports results for both agricultural and domestic wells, (2) and (3) for just agricultural wells, and (3) and (6) for just domestic wells. All regressions are weighted by the DAUCO crop acres and include year and DAUCO by well type fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Construction of New Domestic Wells

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-1.534	-1.021	-0.0657	-0.0128
	(1.582)	(1.535)	(0.0783)	(0.0641)
Harmful Degree Days		0.0774		0.00950*
		(0.0477)		(0.00445)
Growing Degree Days		-0.00782		
		(0.00473)		
Annual Precipitation		0.00734**		0.000417**
		(0.00280)		(0.000139)
Observations	9,660	9,240	9,072	8,876
N Cluster	345	330	324	317
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new domestic wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: Construction of New Agricultural Wells: Municipal and Industrial Surface Water

	OLS		PPML	
	(1)	(2)	(3)	(4)
M&I SW Allocation per Acre	19.71	23.36	1.407	1.459
	(28.88)	(28.91)	(1.300)	(1.257)
Harmful Degree Days		0.115**		0.0143***
		(0.0422)		(0.00287)
Growing Degree Days		0.000191		0.000472
		(0.00839)		(0.000636)
Observations	8,874	8,400	7,540	7,224
N Cluster	306	300	260	258
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Independent variable is surface water allocated (AF per crop acre) for municipal and industrial use, as opposed to agricultural use. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$