External Costs of Climate Change Adaptation: Groundwater Access*

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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). Mitigating 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; Hultgren et al., 2022). Traditionally, adaptations are modeled as internal costs and benefits(Hultgren et al., 2022; Carleton et al., 2022). However, these actions may impose externalities that are disproportionately borne by those least able to engage in mitigating behavior. Little is known about the extent to which 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). Traditionally, this common pool resource has been managed under open-access conditions, leading to inefficiencies from over-extraction (Hotelling, 1931; Ayres, Meng, and Plantinga, 2021). Dependence on this groundwater during times of scarcity may impose additional 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 (Provencher and Burt, 1993; Roseta-Palma, 2002; Brozović, Sunding, and Zilberman, 2010; Pfeiffer and Lin, 2012; Edwards, 2016; Merrill and Guilfoos, 2017). Less well understood are the acute and contemporaneous costs that groundwater pumping may exact on drinking water supplies in surrounding communities. Many rural households rely on private 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.[1] 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 behavior 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 agricultural groundwater wells and back out the intensive margin of response.

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

[1] 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 supply data from over 400 water districts between 1993 and 2020. These detailed data allow us to deploy an instrumental variables 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 may 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 or a 3.2% reduction in groundwater levels across California's aquifers in the subsequent year. 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 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.

This finding brings a new data point on the extent to which adaptation will buffer against the agricultural costs of climate change. Extensive work shows that agricultural outcomes are responsive to fluctuations in weather (Deschênes and Greenstone, 2007; Hagerty, 2021). However evidence on the extent to which adaptation can mitigate these costs is mixed, with some studies pointing to little evidence of adaptation to climate change (Burke and Emerick, 2016; Auffhammer, 2018) and other work suggesting that in the long-run the costs may be cut in half (Hultgren et al., 2022). The latter may occur if agricultural producers adopt new technologies, change the location and types of crops grown, or adjust the quantity and composition of inputs (Sloat et al., 2020; Rosa et al., 2020; Aglasan et al., 2023). 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 amplified if farmers cannot rely on groundwater to buffer against these shocks (Hornbeck and Keskin, 2014; Auffhammer, 2018; Perez-Quesada, Hendricks, and Steward, 2023).

A second central result demonstrates that increases in extreme heat and reductions in surface water availability lead to drinking water well failures in low-income and non-white communities. Our estimates indicate that the surface water reductions and the increase in harmful degree days experienced during the 2021 drought led to a 4 and 5 percentage point increase in the probability of domestic well failures, respectively. A decomposition reveals substantial heterogeneity in who experiences well failures. Low-income and communities of color bear a substantial share of well failures and their associated costs.

Lastly, to explore the mechanisms underpinning the estimated declines in groundwater supplies, we first empirically quantify how new agricultural well construction responds to heat and surface water scarcity, and then back out the intensive-margin response. Surface water reductions cause farmers to respond along the extensive margin, with the reductions of the magnitude experienced in 2021 resulting in the construction of 320 agricultural groundwater wells per year. Using our conceptual model and empirical estimates, we then back out that the intensive margin response and find that these curtailments leads farmers to pump an additional 19 AF from each existing well. Heat also leads to increased groundwater extraction. We find that an additional 23 harmful degree days causes farmers to construct 300 additional groundwater wells and pump 9 AF more from each existing well. This latter result underscores that even if surface water supplies remain unchanged, warming temperatures will alter water resources through increased demand.[2]

Our results bring empirical evidence to bear on how climate change - through the chan-

[2]While climate projections indicate increased year-to-year variation in rainfall, projections on the total amount of precipitation are less clear (Jessoe, Mérel, and Ortiz-Bobea, 2018). In the context of California's water infrastructure, total surface water supplies for agricultural use in California are expected to decrease by 25% by 2060 (Wang et al., 2018).

nels of warming temperatures and more variable and scarce surface water supplies - will affect externalities arising from the open-access management of common pool resources. A longstanding literature documents that open access conditions lead to too much extraction of groundwater at too quick a pace (Hotelling, 1931; Pfeiffer and Lin, 2012; Ayres, Meng, and Plantinga, 2021). Less clear is how climate change interacts with these externalities. Recent work on the water resource impacts of climate change have focused on the link between climate and irrigation, showing increases in irrigation as farmers seek to buffer against warming temperatures and more variable precipitation (Taraz, 2017; Taylor, 2023). Our findings highlight that the externalities from groundwater consumption - as measured by annual changes in depth to the water table and domestic well failures - are exacerbated by climate change and unequally borne by disadvantaged populations.[3]

This paper also adds a new dimension to our understanding about inequities in exposure to environmental costs (Banzhaf, Ma, and Timmins, 2019). A recent literature documents that disadvantaged communities bear a disproportionate burden of pollution and its associated harms, and seeks to identify the distributional implications of environmental regulations intended to reduce pollution (Cain et al., 2023). This work highlights a general reduction in pollution disparities over time and decomposes the relative contribution of command and control and market-based approaches in reducing this gap (Fowlie, Holland, and Mansur, 2012; Bento, Freedman, and Lang, 2015; Shapiro and Walker, 2021; Hernandez-Cortes and Meng, 2023). Less is known about the equity implications of an open-access management regime, which governs many common-pool resources.[4] Our work implies that inequities arise from an open-access management regime, specifically that mitigating behaviors by those with access to capital will impose costs on disadvantaged groups.

[3]Taylor (2023) also quantifies the externality at a global scale from warming temperatures by using GRACE satellite measures to compare changes in thickness over a 12-year period.

[4]Recent work highlights the net benefits of markets relative to open-access management in the context of California groundwater (Ayres, Meng, and Plantinga, 2021).

2 Agricultural Water in California

We evaluate the external costs of mitigating behaviors in the context of California water, a setting where agriculture accounts for 80% of consumptive use, droughts are increasingly frequent and severe, and access to reliable drinking water supplies poses a concern in many rural communities. California is a leading producer of agricultural products in the U.S. and globally, comprising over a third of the nation's vegetables and almost three-quarters of its fruits and nuts (California Department of Food and Agriculture, 2020). One reason for the state's large market share in agricultural production is irrigation. Almost all agricultural acres are irrigated, with over half of the farms using a mix of surface and groundwater sources.

Within the state, agricultural production is heavily concentrated in the San Joaquin Valley (SJV) in central California. The counties located in the SJV are primarily rural and experience some of the highest poverty rates in the country. Many of these households utilize private domestic groundwater wells for drinking water purposes. These domestic wells are relatively shallow, and as a result, are vulnerable to weather driven declines in groundwater levels.

Surface Water Irrigation

Surface water supplies, which account for approximately 60% of irrigation supplies in an average year, exhibit substantial heterogeneity over time and across irrigation districts. Annual state-level surface water supplies are largely determined by fall and winter precipitation in the Sierra Nevada and other local mountain ranges. As the snowpack melts, this runoff is temporarily captured and stored in reservoirs and later delivered to farmers and irrigation districts through a network of canals. Large inter-annual swings in precipitation are endemic to California and lead to meaningful variation in in surface water supplies from year to year.

A complex allocation system dating back to the early 1900s guides the assignment of water across users, and introduces cross-sectional heterogeneity in surface water rights. A user, defined as an irrigation district, will hold an appropriative right to divert water directly from a nearby river or stream and/or possess a long-term contract to water deliveries provided by a state or federal water project.[5] The state operated State Water Project and federally run Central Valley and Lower Colorado River Project comprise the three main surface water projects. Water contracts specify a maximum annual volume of water supplied and a contract priority. This array of water rights and water projects dates back more than 40 years and created an entitlement system where neighboring water districts will obtain surface water from different sources under different contract conditions.

Within an irrigation district, large fluctuations exist in yearly water project deliveries. Each year the government agency managing a water project announces allocation percentages for each contract type. These percentages are based on reservoir levels, environmental conditions and weather and determine how much of the maximum volume an irrigation district will receive. Allocation percentages are announced in advance of planting decisions and are largely based on winter precipitation and reservoir levels. There are 13 different contract types, where the allocation percentage a district receives will differ based on the water project and priority order. As a result, within a year different districts will receive different allocation percentages, depending on the contract type and their appropriative water rights.

The actual surface water deliveries that a district receives 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.

Groundwater Irrigation

Groundwater has traditionally acted as a buffer to fluctuations in surface water supplies. To counter the reduced surface water supplies that accompany droughts, dependence on groundwater

[5] Most agricultural water rights and contracts are held by irrigation districts – local government agencies – which then supply water to farms within their jurisdictions. Within each district, 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.

increases, accounting for up to 80% of water supplies during droughts.

Historically, groundwater has been managed under an open-access regime, with agricultural water use neither monitored, measured nor priced. 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, higher pumping costs, and other negative consequences (Provencher and Burt, 1993; Brozović, Sunding, and Zilberman, 2010; Edwards, 2016). For example, in the San Joaquin Valley of California groundwater levels in some basins have experienced over a 100 foot reduction in the past 10 years (Department of Water Resources, n.d.). Partly in response to these concerns, in 2014 California passed historic groundwater regulation - the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater by 2042.[6]

The primary barrier to increased groundwater use on the extensive margin is the cost to construct a well. The fixed cost 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 (California State Board of Equalization, 2023). 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).

Drinking Water in Rural Communities

While most individuals in California receive residential and drinking water from community water systems, between 3.4 to 5.8% (or 1.3 to 2.25 million) of individuals obtain drinking water from domestic wells.[7] Private domestic well users draw groundwater from aquifers that are shared with

[6]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.

[7]Community water systems are public water systems with over 15 connections and serve greater than 25 people.

domestic and agricultural users. When compared to agricultural wells, domestic wells are shallow and as a result more susceptible to running dry as groundwater tables decline. 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.

As shown in Figure A2, which maps the location of domestic wells throughout the state, these private drinking water wells are concentrated in the agricultural centers of the state, and in particular the San Joaquin Valley. [8] These areas also comprise some of the most economically and socially vulnerable communities in California. Populations in the San Joaquin Valley are 50.2% Hispanic (compared to national average and 18.9%) and 23.2% of households are below the federal poverty line (compared to a national average of 12.9%). Private well failures are also concentrated in relatively low income, rural and non-while communities. This is highlighted in Figure 1 which plots the proportion of reported well failures by income, populations of color and agricultural density.

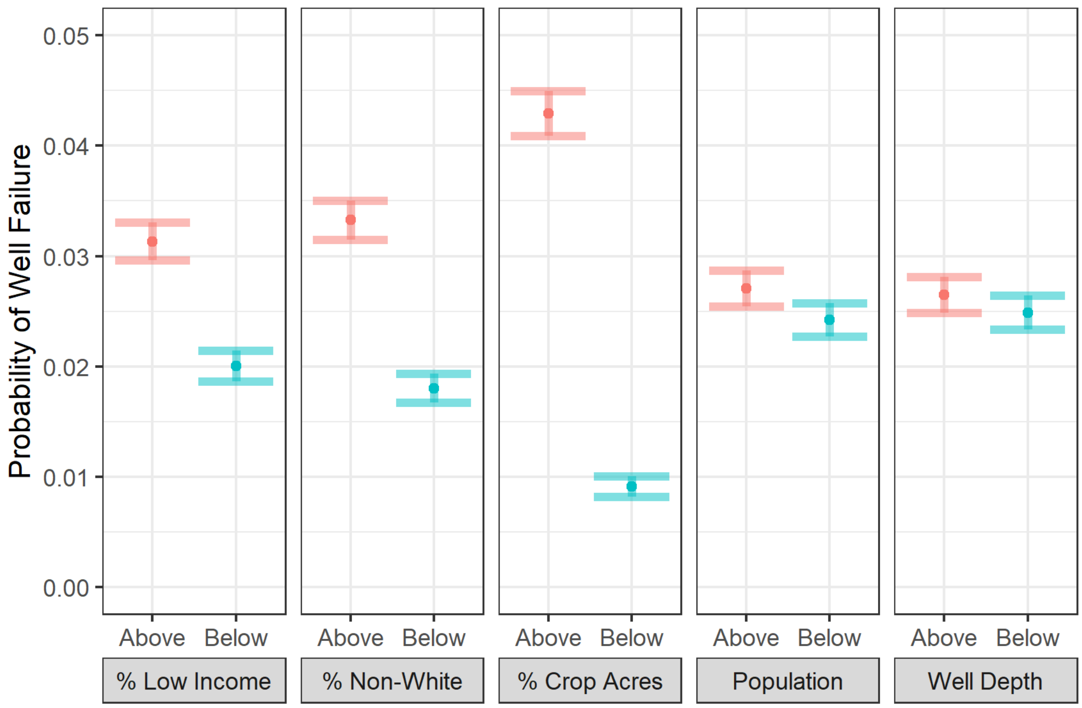
Impacts of Climate Change in California

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 projected to be reduced by 25% by 2060 (Wang et al., 2018). The latter is partly due to increased precipitation volatility and extreme drought risk (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. The implication of this is that even if surface water supplies do not change, extreme heat will lead farmers to demand more water for irrigation (Rosa et al., 2020).

To date, the estimated impacts of climate change on California agriculture are mixed. The

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

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



Note: Figure displays the mean probability of domestic well failure for all domestic wells in California partitioned by above and below median values for socioeconomic, agricultural, and well characteristics. Demographic data come from IPUMS NGHIS (Manson et al., 2022) and are assigned at the census tract levels where the domestic well is located. Low-Income % is the percent of households living below the Federal income thresholds by family size. Error bars report the 95% confidence intervals from a t-test of the well failure probabilities by demographic sub-group.

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). Historically, direct climate damages have been mitigated through adaptive behaviors by farmers (Burke and Emerick, 2016; Hagerty, 2021), like increased irrigation. These behaviors may explain why damages were calculated to be minimal in earlier studies. However, these mitigation channels 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 groundwater levels and access to drinking water. Formalizing the relationship between farmer decisions and depth to the water table allows us to quantify the intensive margin response to heat and surface water shocks as a function of estimated demand parameters and observables.

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 in a year impacts the end of year water stock. If annual groundwater consumption exceeds recharge, $R(s,h)$, then the stock of water in the aquifer declines and the depth to the remaining groundwater stock increases. The depth to the water table (DTW) is given by:

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

which depends on the starting depth to the water table, DTW_0, consumption, and recharge. The effect of an acre-foot of consumption on the depth to the water table is a direct function of the geological characteristics of the aquifer. This is captured by a constant multiplier, κ.[9]

Assume that the farmer experiences a surface water (or heat) shock in a given year, ds (dh). The short-run change in DTW from this shock can be decomposed into three channels:

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

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: $\frac{\partial q}{\partial s}(s,h)$. Lastly, a decrease in surface water irrigation (or an increase in evaporation due heat) will lower recharge, $\frac{\partial R}{\partial s}(s,h)$, since there will be a decrease in the volume of water that drains through the soil into the aquifer below.

This conceptual framework provides us with a pathway to empirically recover lower bounds of the intensive and extensive margins of response to surface water and heat shocks within a single year. 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-

[9]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. 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.

margin effect, $\frac{\partial q}{\partial s}(s,h)$, under given assumptions.[10] This allows us to identify the gross effect of climate shocks as captured by changes in depth to the water table, and decompose the mechanisms behind this effect. We extend this model in section A.2 to incorporate persistent impacts on groundwater levels over future years.

One external damage of declining groundwater tables is 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 1 provides summary statistics and lists the cross-sectional unit of observation for each variable.

[10] As discussed in the results, we calculate average values of q and w based on our data and California agricultural statistics, and impose a hydrologic values for κ and $\frac{\partial R}{\partial s}(s,h)$ consistent with California aquifers.

Table 1: 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.[11] We spatially aggregate these data to the Detailed Analysis Unit by County (DAU by Co or DAUCO) and use the DAU as the unit of observation for surface water deliveries, allocations, and agricultural well construction. DAUs are a construct of The California Department of Water Resources, and delineated by dividing the state's hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis. 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. Our final measure of surface water supplies captures the volume of surface water delivered in AF per crop acre (AF/acre) in the DAUCO.[12]

[11]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.

[12]We standardize water allocations and deliveries by dividing them by cropland acres in each DAUCO. There are a number of reported extreme values of water allocations and deliveries, likely due to measurement error. To account for this, we Winsorize this variable at 10 AF/acre.

Figure 2 displays the variation in surface water allocations across the 390 DAUCOs over three years: 1994, 2006, 2015. In relatively wet years, such as 2006, each DAUCO receives 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

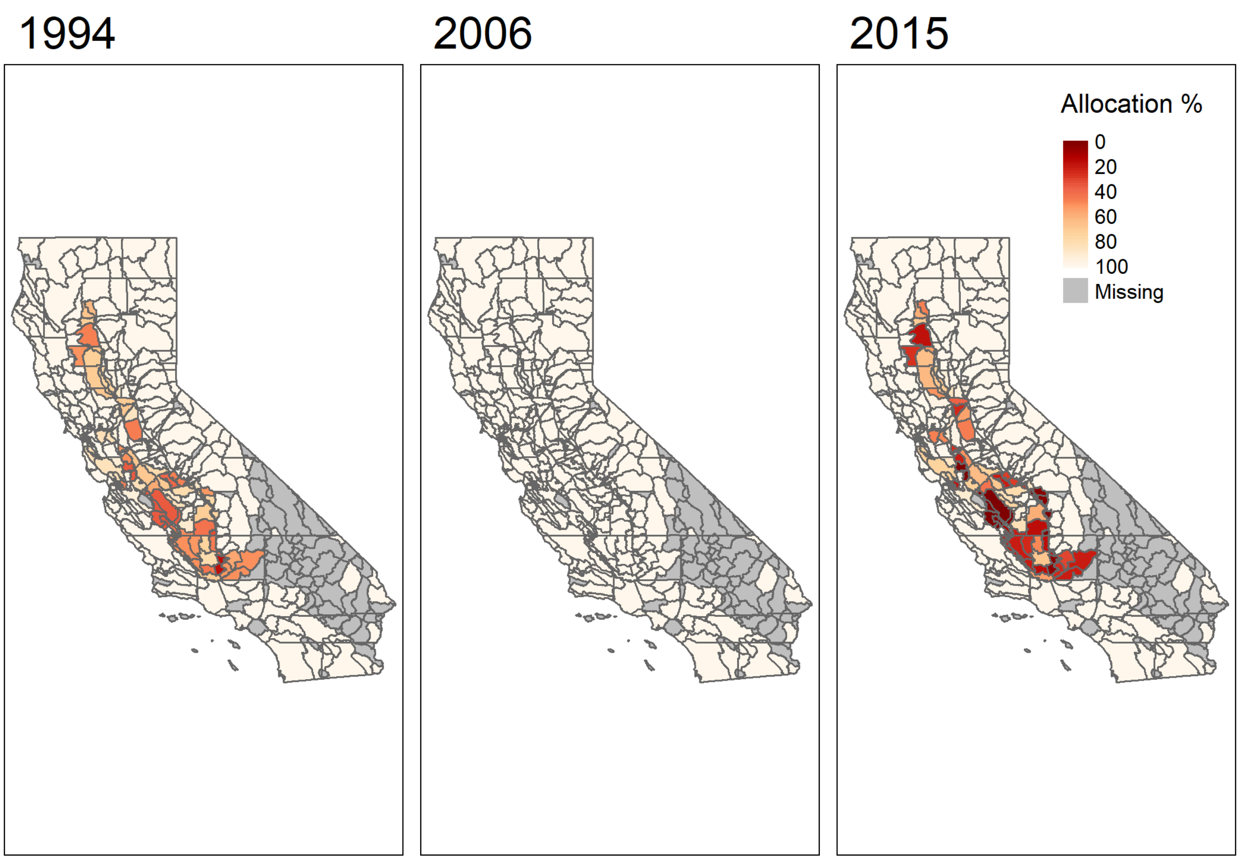
Monitor level measures of the depth to the water table are available from 20,000 monitoring wells between 1993 and 2020. Depth to the water table measures come from two sources: the State Water Resources Control Board's Groundwater Information System and DWR's Periodic Groundwater Level Measurement.[13] Within each monitor-year, we select a single date to measure the depth to the water table. 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 in the preceding year. Year-to-year differences in monitor-level depth measure the change in the depth to the water table.[14]

As shown in Table 1, groundwater levels decline by approximately 4 inches per year on average. This statistic, however, masks substantial temporal and spatial heterogeneity in groundwater levels. Figure 3 illustrates the change in depth to the groundwater in each DAUCO in three

[13]Figure A3 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.

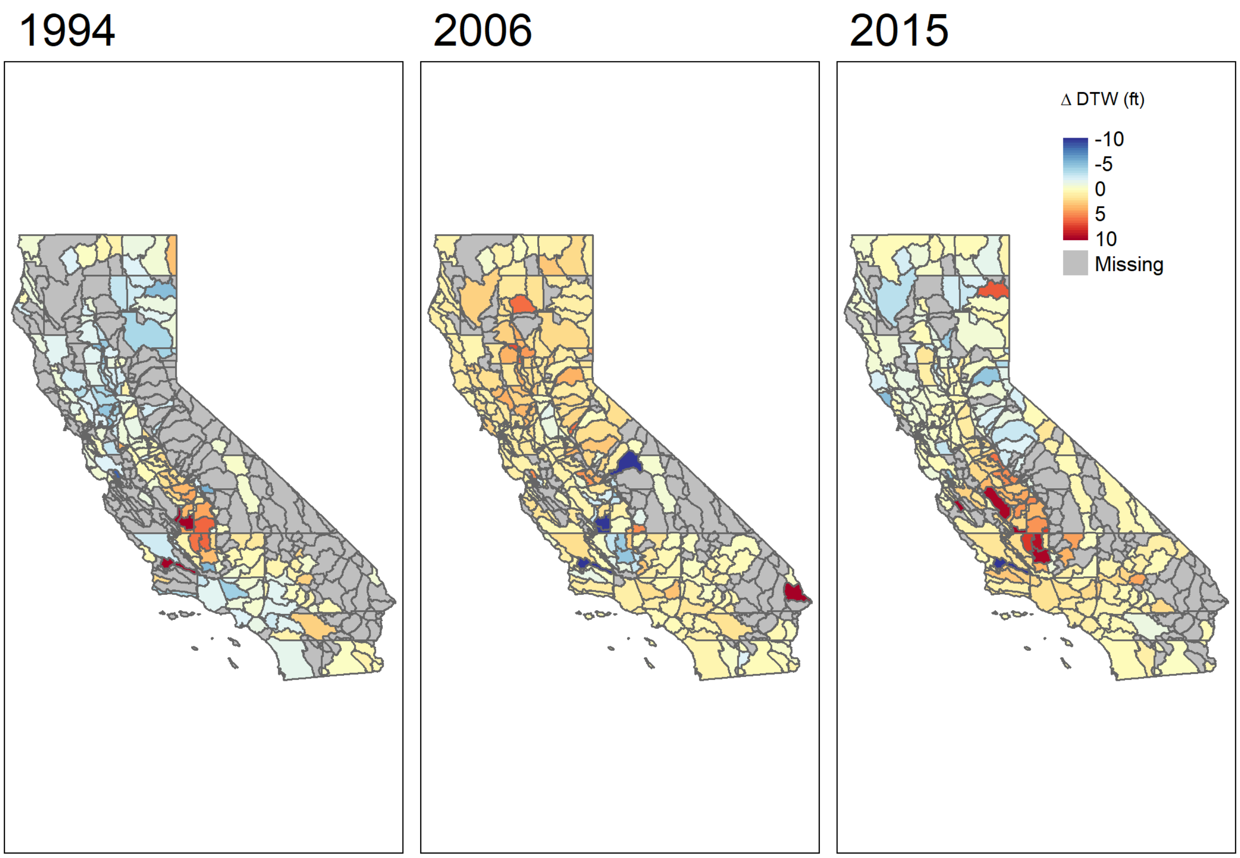
[14]To account for outlier observations, we exclude observations that are more than 1.5 times greater than the inner decile range reported from other monitoring wells in the same DAUCO over our sample. This rule removes observations with drastically different changes in groundwater levels than other local groundwater measures. Some of these outlier observations are the result of a misplaced decimal, while other errors occur from monitor errors. We cannot easily identify the source of error in these data, and for this reason remove these observations to reduce measurement error.

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.

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.

different years. It makes clear that groundwater tables generally decline in the drought years 1994 and 2015, 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 over 10 feet.

Well Construction

We measure the extensive-margin response 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 well depth, intended use, and drilling date.[15] Our final outcome is the count of the total number of new agricultural irrigation wells per DAUCO-year.

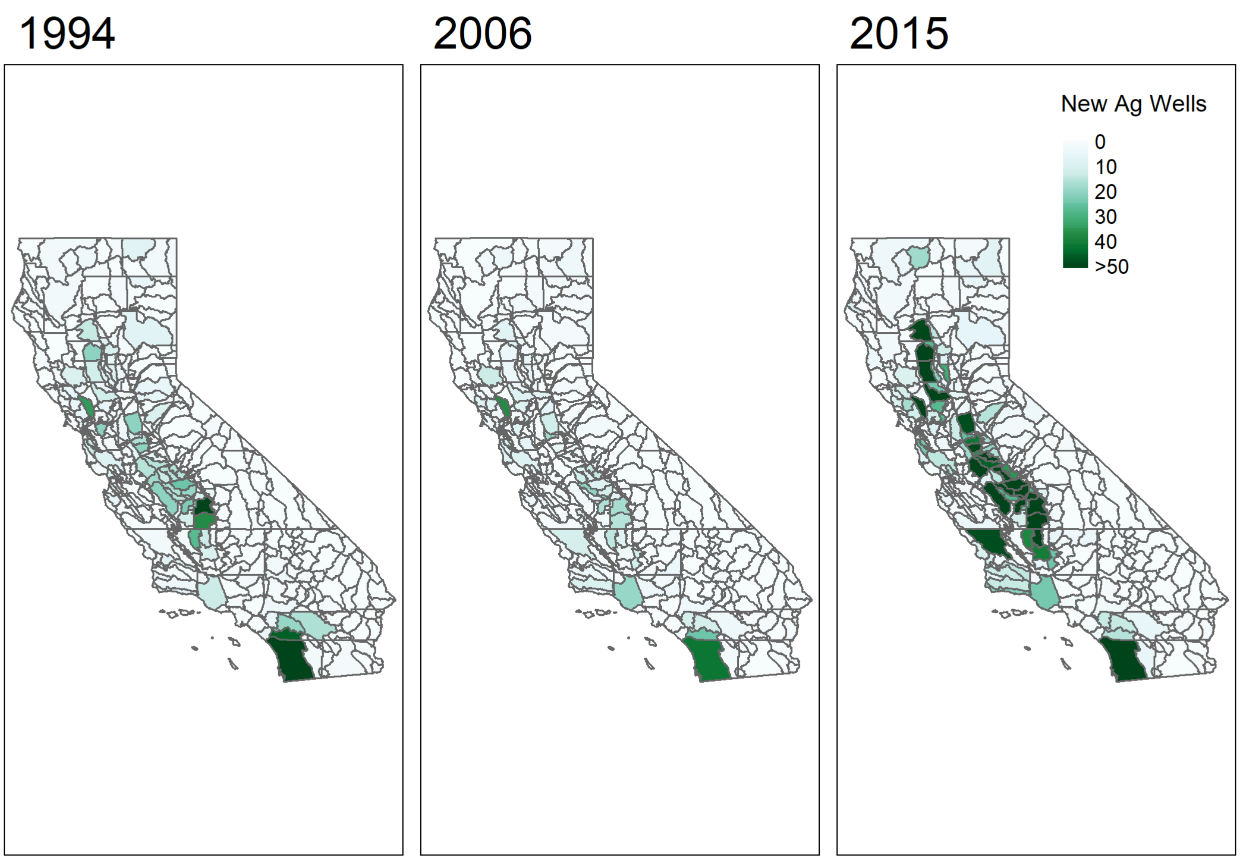
Figure 4 maps new agricultural well construction for the years 1994, 2006, and 2015. New well construction varies from year-to-year and increases in drought years. This activity is also concentrated in the San Joaquin Valley. A visual comparison of Figures 2 and 4 suggests that well construction is more 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 A4, contain the coordinates for the reported dry well, the date the issue started, and if the issue was resolved. Using the Well Completion Report data, we create a panel on the service status of all domestic wells by geographically matching the reported failures to the registered domestic wells. We denote 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.

[15] 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 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.

Since 2014, over 4,000 domestic well failures have been reported. The black outlined region of Figure A4 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 effects of these shocks on access to drinking and agricultural groundwater. 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.

Changes in Depth to the Water Table

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

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

The dependent variable, ΔDTW_{idt}, is the year-to-year change in the depth to the water table for well i in DAUCO region d and year t. It measures the *flow* of groundwater levels at well i, as opposed to the *stock* that is captured in the raw variable DTW_{it}.We have two primary regressors of interest: SWD_{dt} and HDD_{dt}. SWD_{dt} measures surface water deliveries in acre-feet per crop acre in DAUCO region d and year t. Similarly, HDD_{dt} is the annual number of harmful degree days in DAUCO d and year t. The vector X_{idt} measures precipitation and growing degree days; λ_t captures statewide annual shocks and trends; and α_i absorbs fixed well level unobservables. Standard errors are clustered by DAUCO to account for serial correlation among wells within the same district.

The coefficient β_1 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. 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, the regression is weighted by crop acres times the inverse density of monitoring wells per DAUCO.

As previously mentioned, surface water deliveries may be influenced by users. In low surface water allocation years, irrigation districts can affect their total delivery amount by purchasing water on the spot market or drawing from water banks. These behaviors may be correlated with groundwater extraction and bias estimates of equation 6. To account for this, we use surface water allocations as an instrument for surface water deliveries and estimate an instrumental variables model,

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

The instrument SDA_{dt} measures surface water allocations in DAUCO d and yer t; all other variables are defined as before.

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 surface water deliveries. In California, surface water allocations are set ahead of the growing season based on that year's environmental conditions and are not used for any other regulatory decisions. no obvious channel exists through which this assumption would be violated. Second, allocations 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.

Our primary identifying assumption 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 and heat as control variables is motivated by this concern. The insensitivity of the treatment effect to the inclusion and exclusion of time-varying local weather shocks included in X_{it} lends support to this identifying assumption.

Domestic Well Failures

Changes in the depth to the groundwater table may cause domestic wells to run 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 variables model with two-way fixed effects using OLS,

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

The outcome, Y_{idt}, is now a binary outcome indicating whether domestic well i reported failing in year t. All other variables are defined as in 7, with the exception of α_i which denotes domestic well fixed effects. The coefficient estimates of interest, 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.

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 its distribution may be right skewed. 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.

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

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 2. 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 2 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 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 results in a 2 ft decline across California. The results also imply that 2021 levels of extreme heat, holding constant surface water supplies, causes 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 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 3 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

[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 2: 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	561,085	560,931	561,085	560,931
N Groups	83,782	83,762	83,782	83,762
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.

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

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 (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 1.

Figure 5 shows that well failures resulting from weather shocks are concentrated in low-

Table 3: 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		✓		✓

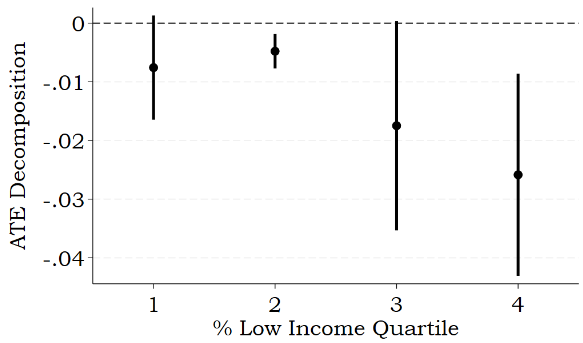
Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed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

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

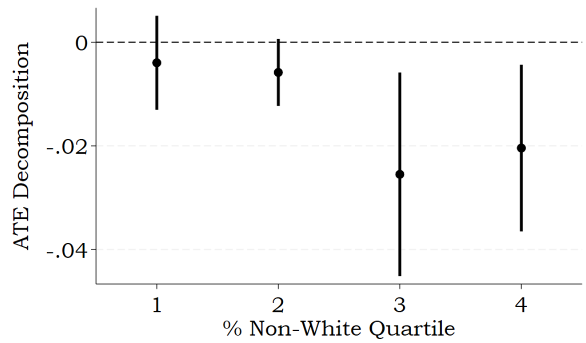
income populations and among people of color. To test for distributional impacts, we decompose the overall treatment effect by subgroup by interacting an indicator for well failure and an indicator for each subgroup. Panels (a) and (c) decompose the effect among percent of low-income quartiles. Similarly, panels (b) and (d) separate the treatment effect into quartiles of percent non-white population, respectively. Both sets of results show that the treatment effects on surface water deliveries and HDD are driven by low-income and nonwhite populations, while higher-income and whiter populations exhibit smaller shares of the overall treatment effect. 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

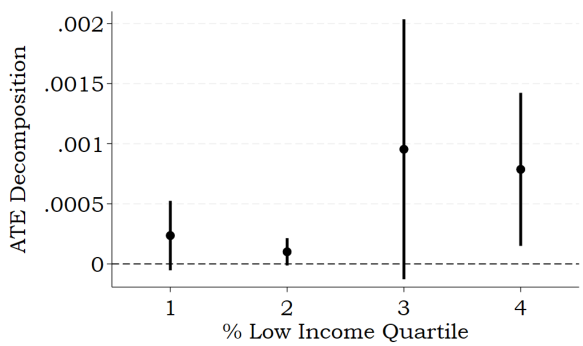
Figure 5: Decomposing Average Treatment Effects (ATE) by Local Demographics



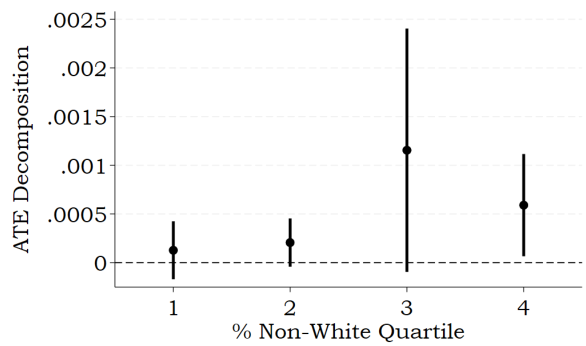
(a) Ag SW Deliveries (AF/acre)



(b) Ag SW Deliveries (AF/acre)



(c) Harmful Degree Days



(d) Harmful Degree Days

Note: Figure shows the share of the treatment effect on surface water and heat by demographic quartile. Dependent variable is a binary outcome if a domestic groundwater reported a failure that year multiplied by demographic quartile identifiers. For panels (a) and (c), the treatment effect on well failures is decomposed by the census tract quartile for the percent of the population that is low-income. Panels (b) and (d) the treatment effect is decomposed by by the quartile of percent of the population that is non-white. All regressions are weighted by the DAUCO crop acres, include year and DAUCO fixed effects, and control for local weather.

can respond to heat and surface water scarcity: the construction of new wells. Table 4 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% 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 because of surface water curtailments and $22 million to construct 294 as the result of extreme heat at a uniform, assumed cost of $75,000 California State Board of Equalization (2023).

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.

Temporal Dynamics

Until this point, our conceptual and empirical models have focused on the effects on groundwater outcomes in the contemporaneous year. Yet, these effects are unlikely to be fully isolated to a single year. Our conceptual model posits that the number of groundwater wells directly impacts consumption and groundwater stock. New well drilling may result in persistent depletion of groundwater stocks in the future periods too as more total wells pump water than in prior years. In this case, the full effect of one year's weather shocks on groundwater levels is the accumulation of the effect as additional pumping occurs in the current year plus future periods. We extend our

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

Table 4: 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.

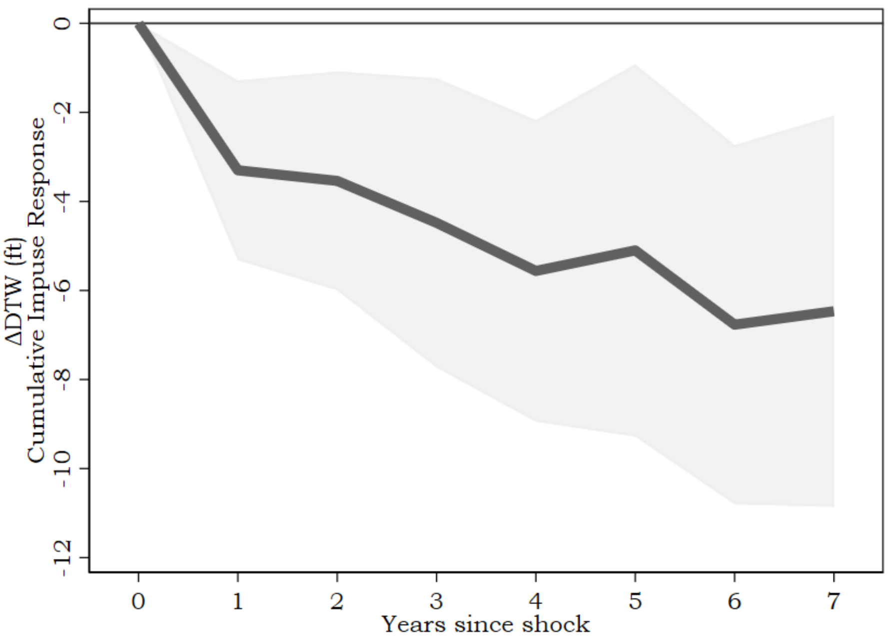
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

conceptual model to demonstrate this point in section A.2.

To explore the dynamic impact on groundwater levels empirically, we estimate a similar model to equation 7 but also include lagged weather shocks measures to explore the persistence and evolution of the effects over time. Figure 6 displays the main findings from this exercise. The results demonstrate that flow of groundwater experiences large changes in the initial year of the weather shock, consistent with Table 2, and groundwater levels also experiences persistent and increasing declines over time. Six years after the initial shock, the cumulative change in groundwater levels is 6.7 (ft) from an initial one AF/acre change in the first year. This effect is more than double the contemporaneous effect of 2.9 (ft).[19]

[19] We are limited to track the full evolution of this effect throughout our sample due to a shrinking sample size and increasingly noisy model with each subsequent lag. For this reason, we limit our results to focus on the six years after the initial shock. However, the lifespan of modern agricultural wells may well exceed 100 years, implying even longer

Figure 6: Cumulative Impulse Response of Surface Water Shocks on ΔDTW



Note: Figure displays the cumulative impulse response of a single surface water shock (AF/acre) in the initial year. Dependent variable is ΔDTW and the dark line reflects the sum of contemporaneous and lagged coefficients on surface water deliveries for each year since the initial shock. Light shading reflects confidence intervals clustered at the DAUCO level.

A separate concern with dynamics 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 A5 and A6 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 well drilling in more detail in

lasting effects on groundwater stock from a single year's well drilling.

section A.2.

Extensive and Intensive Margin Adaptation

Based on the model set forth in equations 3 and A6, we use the point estimates on change in groundwater depth in the contemporaneous year and the future, new well construction, and conservative assumptions about the size of hydrologic coefficients for California 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 four parameters (κ, w, q, and $\frac{\partial R}{\partial s}$) from our conceptual framework as described in equation 3. We assign these values based on our raw data, literature relevant to the Central Valley of California, and methodology from the California DWR 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 in contemporaneous year of the shock, or equivalently, 0.35 AF/acre additional gross groundwater depletion($\frac{dDTW}{ds}(s,h) \times \frac{1}{\kappa}$). Of this total effect, we attribute an upper bound value of 0.18 AF/acre to the potential reduction on recharge so as not to overstate the behavioral contribution.[20] Given our estimates of new agricultural wells drilled in Table 4, we calculate that approximately 0.01 AF/acre of the contemporaneous effect results from new wells, or 81,750 AF statewide. While 0.16 AF/acre of the gross effect is due to the intensification of existing wells, or 1.6 million AF statewide.

Over time, the cumulative effect of this single-year shock persists and grows to 6.77 ft re-

[20] This value is calculated from California DWR Water Balance Data, which reports regional values of recharge as a proportion of total applied water. The annual averages of these values range from 0.07-0.18 AF/acre. For this exercise, therefore, we assume that all of the maximum potential recharge is lost from these weather shocks.

duction in groundwater levels six years later. The persistence can be explained by the permanence of agricultural wells once they are drilled, increasing groundwater extractions in the future even under average future conditions as outlined in section A.2. Over the lifespan of the newly drilled wells, total extraction from the these wells – or the cumulative extensive margin effect – likely far exceeds the intensive margin adjustments to pumping behavior in the contemporaneous year.

Understanding the 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 16% of the lost surface water with groundwater supplies when surface water curtailments are imposed in the contemporaneous year. This helps mitigate the yield effects of the weather shocks, but strains historically unregulated groundwater resources. The increase in the number of agricultural wells from these shocks also is a mechanism for persistent increases in groundwater extractions over the lifespan of these new wells, continually straining groundwater resources in the future and imposing external costs to other users of groundwater. Adaptation through both the extensive and intensive margin to these shocks implies 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

Groundwater serves as a critical common-pool resource for the agricultural industry and supplies drinking water to millions of residents in California. This paper illustrates that climate change has accelerated groundwater depletion, exacerbated externalities, and will continued to do so if poorly regulated. We show that this is driven by additional extraction by farmers as they rely more heavily on groundwater to mitigate surface water scarcity and extreme heat. This behavior limits the short-run agricultural costs of weather fluctuations but imposes external costs on domestic well owners. Importantly, the costs are heavily born by people of color and low-income households.

The findings from this study are directly relevant to the management of groundwater, which is largely unrelated across the world. In California, the Sustainable Groundwater Management Act (SGMA), which was passed in 2014 but has yet to take hold, is a key legislation aimed at curbing groundwater depletion. SGMA depends on local agencies and boards to monitor and implement management plans, which has resulted in a patchwork of policy mechanisms and oversight. It remains uncertain whether these localized plans will efficiently and sustainably manage the State's groundwater and eliminate the externalities documented in this paper (Bruno and Hagerty, 2023). However, given that restrictions or moratoria on new well drilling are not regulatory instruments in these management plans, the evidence of this paper would suggest that these externalities may persist despite this legislation, especially in drought years.

Outside of the context groundwater, this paper demonstrates that adaptive behaviors to shield against the damages of climate change may impose costs on others who are unable to respond. While adaptation costs are conventionally included when costs of climate change accounting, the externalities from adaptation are omitted from these figures. Additionally, as climate adaptation occurs in other sectors (e.g. energy, healthcare, manufacturing), it is imperative for policymakers to ensure that the actions taken to limit direct climate change damages are not unintentionally imposing costs on others.

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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.

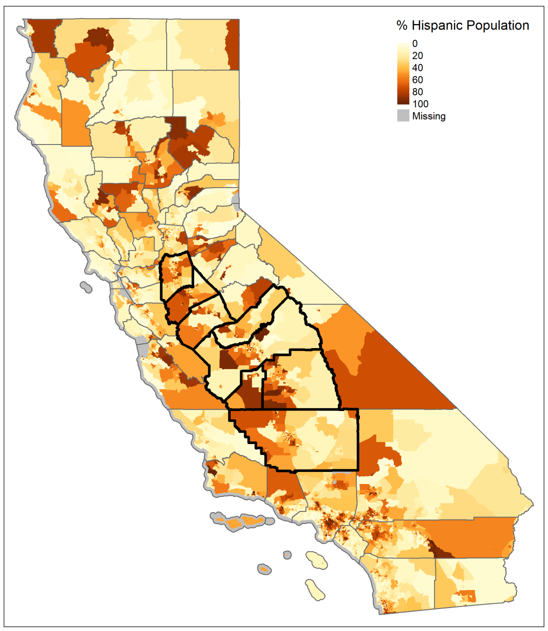
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Parameter Values for Decomposition

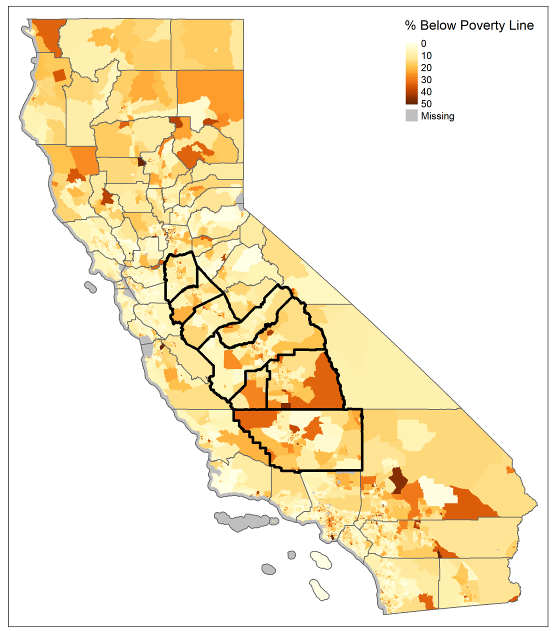
Parameter	Value	Units	Description	Source
$\frac{dDTW}{ds}(s,h)$	-2.91	ft	Gross change in DTW per AF/acre change in surface water	Table 3 Column 4
$\frac{dDTW_T}{ds_t}(s_t)$	-6.77	ft	Cumulative future change in DTW per AF/acre change in surface water	Figure 8
κ	8.33	unitless	Inverse aquifer yield coefficient	Department of Water Resources (2020)
$\frac{\partial R}{\partial s}$	0.18	unitless	Upper bound recharge coefficient. Change in groundwater recharge per AF/acre reduction in applied water.	Author's calculation from California DWR Water Balance Data
$\frac{\partial w}{\partial s}$	-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
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: Population Demographics in California



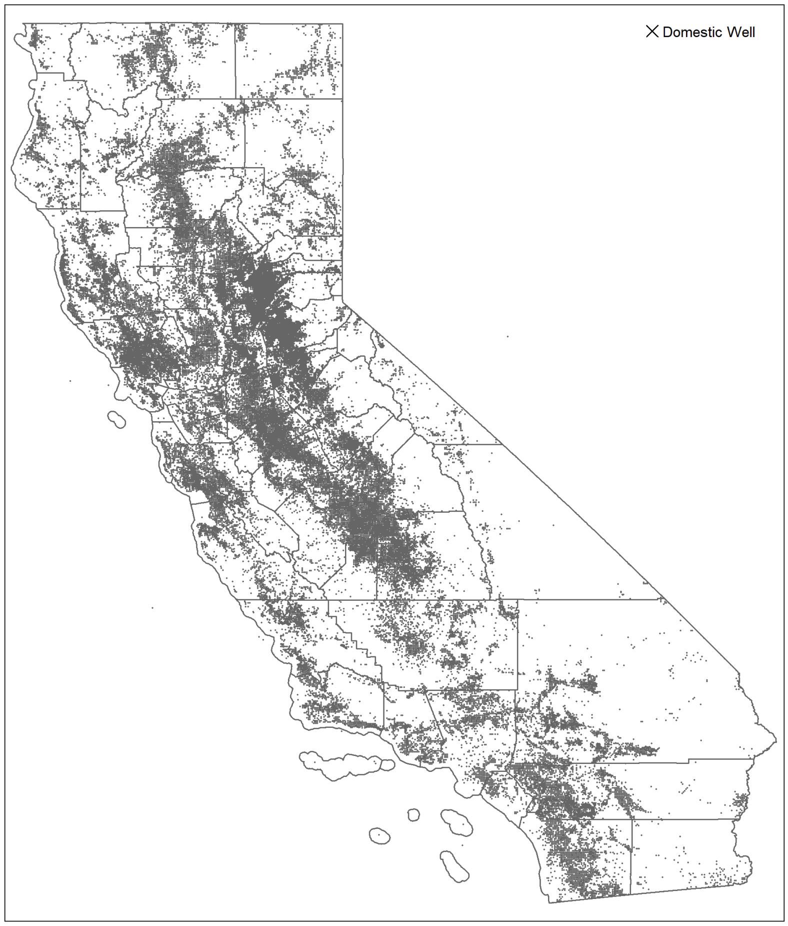
% Hispanic Population
(a)



% Population below poverty line
(b)

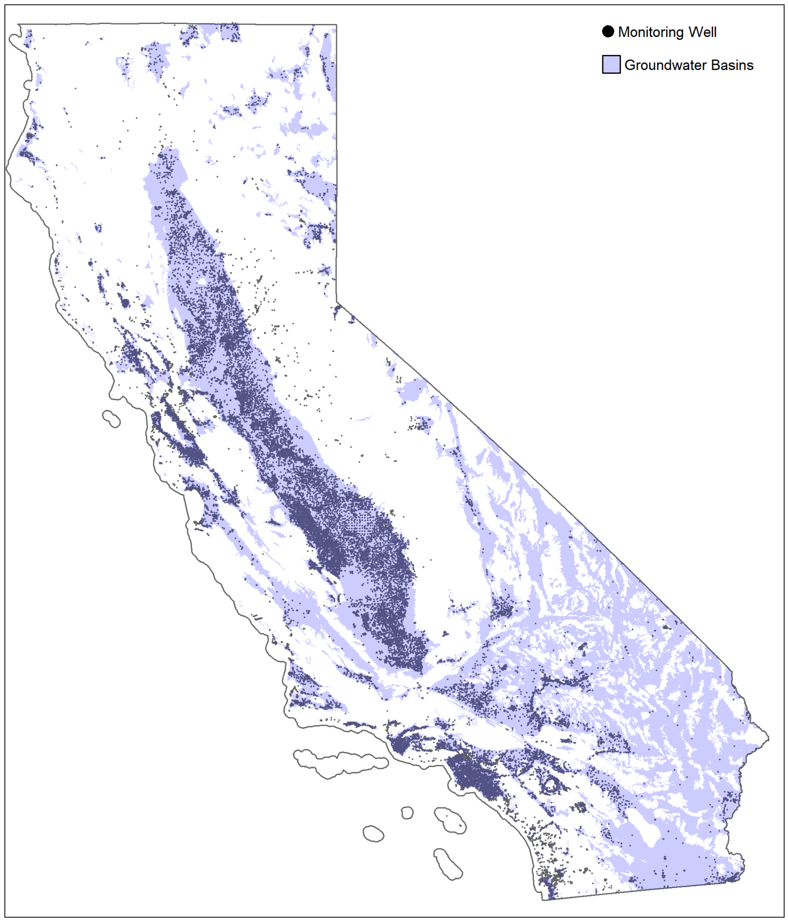
Note: Figure displays demographics at the census tract level using data from 2020 (Manson et al., 2022). Panel (a) plots the percentage of the population that identifies as Hispanic. Panel (b) plots the percentage of households that fall below the federal poverty line for their household size. Bold county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

Figure A2: Location of Domestic Wells



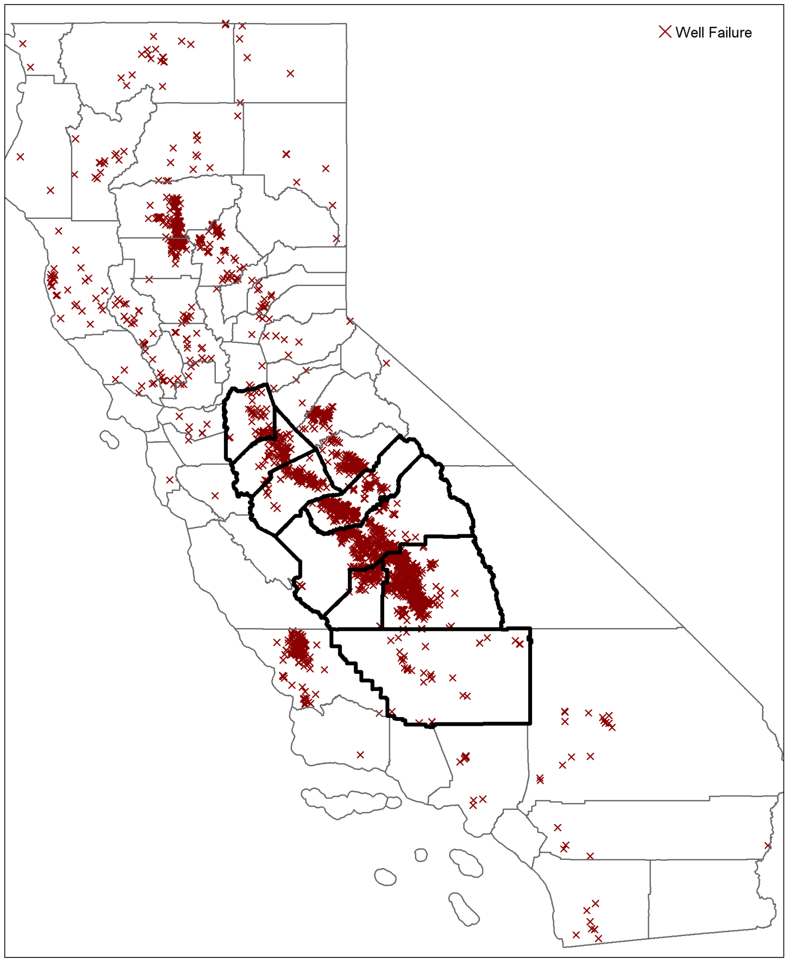
Note: The figure shows a location domestic groundwater wells constructed. Data are from Well Completion Reports from DWR.

Figure A3: 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 A4: 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 Temporal Dynamics

As discussed in the paper, the decision to drill a well and the subsequent impacts from that action are inherently dynamic. In this section, we expand our base conceptual model to incorporate a time element and test emprically the size and pattern of these effects over time.

Dynamic Conceptual Model

Consumption in year t is given by the number of active wells pumping at time t and the average amount pumped from each well. For this expansion, we only focus on the effects for surface water shocks, but symmetrical analysis could be shown for heat shocks:

$$C_t(s_t) = w_t(s_t) \times q_t(s_t) \tag{A1}$$

The number of wells in each period depends on the number of wells in the prior period. Surface water affects only the number of new wells in year t:

$$\begin{aligned} w_t(s_t) &= w_{t-1} + \Delta w_t(s_t) \\ &= w_{t-2} + \Delta w_{t-1}(s_{t-1}) + \Delta w_t(s_t) \\ &= w_0 + \sum_{\tau=1}^{t} \Delta w_\tau(s_\tau) \end{aligned} \tag{A2}$$

Future groundwater stock is a function of that year's consumption and each preceding year's consumption:

$$\begin{aligned} DTW_t(s_t) &= DTW_0 + \kappa C_t(s_t) - R_t(s_t) \\ DTW_{t+1}(s_t, s_{t+1}) &= DTW_0 + \kappa\big(C_t(s_t) + C_{t+1}(s_{t+1})\big) - \big(R_t(s_t) + R_{t+1}(s_{t+1})\big) \\ DTW_T(s_t, \ldots, s_T) &= DTW_0 + \kappa \sum_{\tau=t}^{T} C_\tau(s_\tau) - \sum_{\tau}^{T} R_\tau(s_\tau) \end{aligned} \tag{A3}$$

But consumption from one period to the next is linked by the fact that wells are persistent once built.

$$
\begin{aligned}
DTW_T(s_t,...,s_T) = & \quad DTW_0 + \kappa \sum_{\tau=t}^{T} C_\tau(s_\tau) - \sum_{\tau}^{T} R_\tau(s_\tau) \\
= & \quad DTW_0 + \kappa \sum_{\tau=t}^{T} q_\tau(s_\tau) w_\tau(s_\tau) - \sum_{\tau}^{T} R_\tau(s_\tau) \\
= & \quad DTW_0 + \kappa \sum_{\tau=t}^{T} q_\tau(s_\tau) \Big(w_0 + \sum_{u=t}^{\tau} \Delta w_u(s_u) \Big) - \sum_{\tau}^{T} R_\tau(s_\tau)
\end{aligned} \tag{A4}
$$

Expanding the sums for convenience, to keep current year shocks separate from later year shocks:

$$
\begin{aligned}
DTW_T(s_t,...,s_T) = DTW_0 + \kappa \sum_{\tau=t}^{T} q_\tau(s_\tau) \Big(w_0 + \sum_{u=t}^{\tau} \Delta w_u(s_u) \Big) - \sum_{\tau}^{T} R_\tau(s_\tau) \\
= DTW_0 + \kappa q_t(s_t) w_t(s_t) + \kappa \sum_{\tau=t+1}^{T} q_\tau(s_\tau) \Big(w_t(s_t) + \sum_{u=t+1}^{\tau} \Delta w_u(s_u) \Big) - \sum_{\tau}^{T} R_\tau(s_\tau)
\end{aligned} \tag{A5}
$$

Then, assume a shock to surface water occurs in time t. The effect on future groundwater levels can be decomposed as:

$$
\frac{dDTW_T}{ds_t} \cdot \frac{1}{\kappa} = w_t(s_t) \frac{dq_t(s_t)}{ds_t} + \Big(q_t(s_t) + \sum_{\tau=t+1}^{T} q_\tau(s_\tau) \Big) \frac{\partial w_t(s_t)}{\partial s_t}, \tag{A6}
$$

where $w_t(s_t) \frac{dq_t}{ds_t}(s_t)$ represents the current year intensive margin shock, $q_t \frac{\partial w_t}{\partial_t}(s_t)$ is current year extensive margin impact, and $\frac{\partial w_t}{\partial_t} \sum_{\tau=t+1}^{T} q_\tau(s_\tau)$ is the cumulative extensive margin impact.

Dynamic Empirical Estimation Results

Table A4 reports the dynamic effects up for up to 3 lag shocks on surface water deliveries and harmful degree days. This table reflects the same model and pattern illustrated in figure 6. The summed cumulative effect of surface water deliveries on changes in depth to the water table is largest in the initial year, but persists and gradually increases with higher ordered lags.

Tables A5 and A6 consider the dynamics of agricultural well drilling. In Table A5, we report the results a linear IV for well construction, similar to columns (1) and (2) of table 4 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 A6 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. 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 A4 reports estimates of changes in groundwater depth (ΔDTW) regressed on lagged weather shocks.

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.

A.3 Additional Empirical Specifications

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 4 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

Table A4: Lagged Changes in Groundwater Depth

	(1)	(2)	(3)	(4)
	ΔDTW			
Ag SW Deliveries (AF/Acre)	-2.914*	-2.716*	-3.121**	-3.188*
	(1.174)	(1.080)	(1.102)	(1.242)
L.Ag SW Deliveries (AF/Acre)		0.220	-0.258	-0.135
		(0.634)	(0.672)	(0.803)
L2.Ag SW Deliveries (AF/Acre)			-0.701	-1.216
			(0.765)	(0.792)
L3.Ag SW Deliveries (AF/Acre)				-0.520
				(0.381)
$\sum \beta_{deliveries}$	-2.914	-2.496	-4.080	-5.058
$p_{deliveries}$	0.0130	0.00414	0.0000763	0.0000808
Harmful Degree Days	0.0309**	0.0187	0.0181	0.0145
	(0.0115)	(0.0140)	(0.0127)	(0.0123)
L.Harmful Degree Days		0.0223*	0.0252*	0.0299*
		(0.0105)	(0.0104)	(0.0126)
L2.Harmful Degree Days			-0.0114	-0.0159
			(0.00741)	(0.00994)
L3.Harmful Degree Days				0.00535
				(0.0101)
$\sum \beta_{hdd}$	0.0309	0.0410	0.0319	0.0338
p_{hdd}	0.00740	0.00693	0.0393	0.0298
Observations	560,931	421,251	321,384	246,159
N Cluster	282	277	269	260
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	✓	✓	✓	✓

Note: Dependant 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 A5: 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 A6: 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 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) Both	(2) Ag	(3) Domestic	(4) Both	(5) Ag	(6) 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)
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.

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