External Costs of Climate Adaptation: Groundwater Depletion and Drinking Water*

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Abstract

Adaptation to environmental change can carry negative externalities. We document one such case: farmers in California respond to heat and drought by extracting more groundwater, harming access to drinking water for nearby residents. Using yearly variation we show that surface water scarcity and heat increase agricultural well construction, groundwater depletion, and domestic well failures, and that well construction accounts for a large share of the latter effects. In our setting, adaptation also exacerbates inequality. Effects on domestic well failures are concentrated in low-income and Latino communities. Climate damage estimates may be incomplete without accounting for the external costs of adaptation.

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1 Introduction

The effects of climate change are projected to be large in magnitude and broad in reach (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005; Schlenker and Roberts, 2009; Dell, Jones, and Olken, 2012; Lobell, 2014; Graff Zivin and Neidell, 2014). Efforts to quantify the social costs of these climate effects must estimate not only the direct effects of weather shocks and the extent to which adaptation actions can reduce these damages (Barreca et al., 2016; Burke and Emerick, 2016), but also the costs of this adaptation (Carleton et al., 2022; Hultgren et al., 2022). An aspect overlooked so far is that adaptation by individuals may have social costs that differ from the private costs. If adaptation has externalities, then current approaches may understate the full social costs of climate change. And since many negative externalities are already disproportionately borne by vulnerable groups (Banzhaf, Ma, and Timmins, 2019), the external costs of adaptation may constitute yet another way in which climate change exacerbates existing inequities (Carleton and Hsiang, 2016).

This paper empirically documents an important case in which climate adaptation has external costs. We show that actions to reduce the costs of environmental change in one sector impose harm on another group that is already socioeconomically disadvantaged. Our context is groundwater in California, a natural resource that provides irrigation for agricultural production as well as drinking water for rural households. Nearly all agriculture in California is irrigated, from both surface water sources (delivered via canals and rivers) and groundwater (pumped locally from wells). As in most other parts of the United States and the world, groundwater extraction in California is largely unregulated and unmonitored (Edwards and Guilfoos, 2021; Ayres, Meng, and Plantinga, 2021). The vast majority of this extraction is used for irrigation, and many areas that depend heavily on groundwater have experienced water table decline (Department of Water Resources, 2020, n.d.).

One important consequence of groundwater depletion is that it can harm access to drinking water for rural households that rely on private groundwater wells for domestic purposes. Domestic wells tend to be shallower than agricultural wells, and therefore, more susceptible to failing (i.e., running dry) as groundwater tables fall. In California, domestic wells are also concentrated in disadvantaged communities comprised of low-income households and people of color.[1] Access

[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.

to drinking water supplies among disadvantaged communities is a growing concern, and the links between environmental conditions, agricultural groundwater extraction, and domestic well failures remain unclear (Pauloo et al., 2020).

Our overall thesis is that farmers in California respond to heat and drought by increasing groundwater extraction, which harms access to drinking water in low-income and Latina/o communities. We build the case for this thesis through several steps of empirical analysis. First, we study how environmental conditions affect the outcomes that carry costs, showing that heat and surface water scarcity cause groundwater levels to decline more rapidly and domestic wells to fail more often. Then, we provide evidence that these damaging effects are due at least in part to adaptation actions taken by agricultural producers. Because data on groundwater extraction itself is unavailable, we focus on the extensive margin, showing that the construction of new agricultural wells speeds up in response to heat and water scarcity. Finally, we argue that the remaining steps in the causal chain are mechanical, and we use known physical relationships to quantify the contribution of the extensive margin to overall damages.

Our empirical approach uses year-to-year variation that differs across locations to identify the effects of surface water scarcity and high temperatures on groundwater levels, domestic well failures, and agricultural well construction. 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 wells. We combine these data with district-level weather and surface water supply data from about 400 water districts between 1993 and 2020. Because farmers and their water districts have some ability to influence their surface water, we instrument for surface water deliveries using water allocation rules that are set annually by regulators based on environmental conditions. Two-way fixed effects control for local fixed differences (such as historical water rights) and state-level shocks (such as recessions) that may affect water access and producer decisions.

Our research design measures the consequences of adaptation to transient shocks to environmental conditions, not of adaptation to long-term shifts.[2] We make this choice because of the econometric challenges involved in isolating true adaptation to climate change, and much of the existing literature on climate adaptation makes a similar choice (Deschênes and Greenstone,

[2]In the framework of Lemoine (2023), the responses we study are primarily a combination of ex-post adaptation (to realized but unforecasted shocks to temperatures and surface water) and ex-ante adaptation to short-run shocks (in response to forecastable information about temperatures and surface water within a year).

2007; Dell, Jones, and Olken, 2012; Blanc and Schlenker, 2017). Still, we argue that our results carry implications for climate change in the same way that the weather impacts literature does more generally. If agricultural producers exacerbate groundwater depletion in response to heat and drought now, then they are likely to also do so in response to an increase in the frequency of heat and drought. This distinction is not crucial for our main point: that the ways producers respond to changes in environmental conditions can exacerbate negative externalities.

Our first result is that surface water scarcity and extreme heat cause groundwater levels to fall more rapidly than usual. To put our estimates into quantitative context, we scale them to the magnitude of a recent drought in 2021. Our results indicate that surface water scarcity equal to average scarcity in 2021—0.7 acre-feet (AF) less than average—causes groundwater levels to fall by 2 ft more than usual in the same year. The effect of this one-year shock persists over time, with groundwater levels dropping an additional 4.7 ft more than usual in the subsequent six years. Heat exposure equal to average exposure in 2021—23 harmful degree days (HDD) more than average—causes groundwater levels to fall by 0.7 ft (8 in) more than usual.

Our second result is that surface water scarcity and extreme heat increase the rate at which domestic wells fail. We estimate that the surface water scarcity and extreme heat experienced during the 2021 drought raised the share of domestic wells that failed in the same year by 4 and 5 percentage points, respectively. Importantly, we find that the overwhelming majority of the domestic well failures that result from water scarcity and heat occur in low-income communities and communities of color. Because well failures are well-understood in hydrology to be a mechanical result of declining groundwater levels (Pauloo et al., 2020), we can say that heat and drought result in faster groundwater depletion, which causes large numbers of domestic wells to fail, and the costs are concentrated in communities that are already disadvantaged.

After showing that environmental shocks harm groundwater levels and drinking water access, we turn to establishing a mechanism. Our third result is that both surface water scarcity and extreme heat increase the number of new agricultural wells constructed in the same year. Surface water scarcity equivalent to the 2021 drought results in 320 additional new agricultural wells per year, a 32% increase in well construction relative to the usual pace. To understand the final link in the causal chain—how new wells affect groundwater depletion—we lay out a simple conceptual model that decomposes the observed effect on groundwater levels into three channels: the intensive margin response (extracting more per well), the extensive margin response (building more wells), and recharge. Using this model and our empirical estimates, we estimate that 58% of the effect of surface water scarcity on groundwater levels operates through the extensive margin of agricultural well construction. Since an observable choice variable of producers accounts for a substantial share of the damaging effects of environmental shocks, our results imply that adaptation can carry external costs.

Our central contribution is to empirically illustrate a case in which adaptation to climate change can produce negative externalities that are quantitatively important. We argue the external costs of adaptation should be considered in both estimates of the social cost of carbon as well as the design of climate adaptation policy. The literature on climate impacts recently has made progress in quantifying the costs of adaptation in addition to the benefits (Schlenker, Roberts, and Lobell, 2013; Carleton et al., 2022; Hultgren et al., 2022), but adaptation is typically modeled as a choice involving only private tradeoffs. If agents adapt in part by offloading costs to other parties without their consent, as they do in our setting, then profit-maximizing behavior will result in *more* adaptation than is socially optimal. A sector-by-sector accounting of climate damages that ignores externalities will then yield an over-optimistic view of the scope for adaptation and understate the costs of climate change.

Our results also bring empirical evidence to bear on how climate change will affect externalities induced by 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 show that the externalities from groundwater consumption are exacerbated by the types of environmental conditions likely to worsen under climate change, increasing the value of sound resource management.[3] In short, groundwater management policy is climate adaptation policy.

Finally, 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 seeks to identify the distributional implications of environmental regulations intended to reduce pollution (Cain et al.,

[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.

2023). This work highlights trends in pollution disparities over time and decomposes the relative contribution of command-and-control and market-based approaches in explaining changes in 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 shows that adaptive behaviors under open-access management can exacerbate inequities when those with access to capital impose costs on disadvantaged groups.

2 Agriculture and Water in California

The context we study is California, 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 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 use 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 variation 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.

[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).

Large inter-annual swings in precipitation are endemic to California and lead to meaningful variation 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, holds an appropriative right to divert water directly from a nearby river or stream and/or possesses 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 Project 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 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 receives. 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 differs based on the water project and priority order. As a result, within a year different districts 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]

To increase groundwater irrigation on the intensive margin, a producer simply pumps more water from an existing well. The main variable cost is the electricity required to power the well; it scales roughly proportionally with both water quantity and depth. However, any single well exhibits declining marginal yields in both pumping duration and power.

To increase groundwater irrigation on the extensive margin, a producer drills a new well. They would do so either to irrigate more than existing wells can support, or if groundwater tables fall below the depth of existing wells. The fixed cost of well construction varies widely based on the completed drilled depth and intended use. Residential domestic wells are typically between 100 and 300 ft deep and cost approximately $10,000. Agricultural wells are drilled between 300 and 500 ft deep on average and cost about $75,000, but can cost upwards of $300,000 for high-capacity wells (California State Board of Equalization, 2023). They also are drilled with a wider diameter than residential wells to allow for higher flow rates. Modern material and construction of wells allows for their lifespan to often exceed 100 years. New wells are required to be reported to the state Department of Water Resources (DWR) and are typically constructed in under a week (Central Valley Flood Protection Board, 2020).

Drinking Water in Rural Communities

Most individuals in California receive residential and drinking water from community water systems, but many rural communities obtain drinking water directly and exclusively from private

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

domestic wells.[7] Private domestic well users draw groundwater from aquifers that are shared with agricultural users. Compared with agricultural wells, domestic wells are typically shallower and therefore more susceptible to failing, or 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.

Private domestic wells are concentrated in agricultural regions of California and the San Joaquin Valley in particular (see Figure A1).[8] These areas also comprise some of the most economically and socially vulnerable communities in California (see Figure A2). Populations in the San Joaquin Valley are 50.2% Hispanic (compared to a national average of 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-white communities, as shown in Figure 1.

Impacts of Climate Change in California

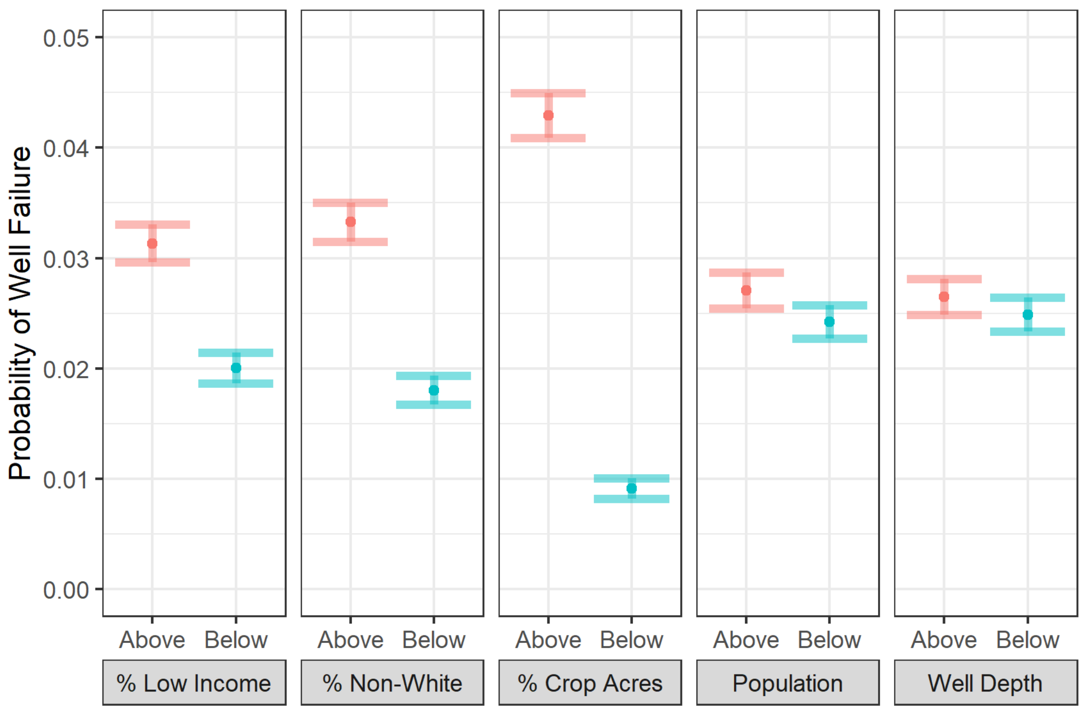
Water scarcity in California is expected to be exacerbated by climate change. While climate models project only modest changes in the mean annual precipitation, the amount of water available in reservoirs and canals for irrigation is projected to be reduced by 25% by 2060 (Wang et al., 2018). The latter is partly due to increased precipitation volatility and insufficient infrastructure to conserve water in reservoirs in the wettest years (Diffenbaugh, Swain, and Touma, 2015; Swain et al., 2018). 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 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;

[7]Community water systems are public water systems with over 15 connections and serve more than 25 people. Between 3.4 and 5.8% (or 1.3 to 2.25 million) of Californians use private domestic wells (Pace et al., 2022)

[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 Safe Drinking Water Act.

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



Note: Figure displays the mean probability of domestic well failure. Estimates and 95% confidence intervals are from a linear probability model, where well failure is regressed on indicators for whether the census tract is above or below median values for socioeconomic, agricultural, and well characteristics. Demographic data for the Census tract in which each well is located come from IPUMS NGHIS (Manson et al., 2022). "% Low-Income" is the percentage of households with income below federal poverty thresholds set by the Census Bureau.

Hagerty, 2021), including increased irrigation. These behaviors may explain why some earlier studies calculated minimal damages. 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 simple conceptual framework based in physics to clarify the relationships between farmers' responses to heat and surface water, groundwater levels, and access to drinking water. This framework will later allow us to quantify the intensive-margin response to heat and surface water shocks despite the lack of data on groundwater extraction.

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 affects 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:

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

which depends on the starting depth to the water table DTW_0, consumption, and recharge. The effect of one AF 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]

[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 storativity, a physical property of an aquifer. For an unconfined aquifer like much of the Central Valley, storativity is also equivalent to specific yield, which measures 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 volume of the aquifer can hold water. The other 88% is composed of porous rock and

Consider a shock that reduces surface water supplies by a marginal amount ds in a given year (alternatively, a shock that increases exposure to heat by dh). The marginal change in DTW that results from this shock can be decomposed into three channels:

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

First, farmers may drill new irrigation wells and pump from them (the extensive margin): $\frac{\partial w}{\partial s}(s,h)$. Second, farmers may extract more groundwater from existing wells (the intensive margin): $\frac{\partial q}{\partial s}(s,h)$. Third, recharge is affected, $\frac{\partial R}{\partial s}(s,h)$, since if less total irrigation water is applied to cropland, less water drains through the soil into the aquifer below.[10]

The logic extends to well failures, since they are a physically deterministic function of the local groundwater depth (Pauloo et al., 2020). We can write the probability of well failure as $F = F(DTW) = F(DTW(s,h))$. When the local water table falls below the depth of a domestic well, the well runs dry and fails. Thus, the share of wells that fail as the result of a surface water shock is proportional to the effect on depth-to-water:

$$\frac{dF}{ds}(s,h) = \frac{\partial F}{\partial DTW}\frac{\partial DTW}{\partial s}(s,h) \tag{4}$$

Equations 3 and 4 allow us to quantify the margins of response to surface water and heat shocks within a single year. They also enable us to back out the intensive-margin effect, even though groundwater extraction is not directly observable, because we observe or estimate the other terms.

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.

sediment.

[10]For a heat shock, recharge also falls because heat increases evaporation, meaning that less of the applied water makes its way into the aquifer.

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: Table reports the number of observations, units of 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 per crop acre (AF/acre).

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 geographic units called DAUCOs, the spatial intersection of DWR-defined "Detailed Analysis Units" (DAU) and counties (CO), and use the DAUCO as the unit of observation for surface water deliveries, allocations, and agricultural well construction. [12] Water allocations measure how much water a DAUCO is slated to receive at the beginning of the year based on rights, contracts, and that year's snow pack and reservoir levels. Deliveries reflect how much water a DAUCO actually receives by the end of the year. Our final measure of surface water supplies captures the volume of surface water delivered in AF per crop acre (AF/acre) in the DAUCO.[13]

Figure 2 displays the variation in surface water allocations across the 390 DAUCOs in three

[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 for analysis.

[12] DWR uses DAUs to subdivide the state's hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis.

[13] 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 minimize their influence, we Winsorize this variable at 10 AF/acre.

different years. 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 seniority of rights. This occurs because of weather-induced reductions in surface water availability. Adjacent water districts can receive very different allocations, and these differences in allocations vary year to year.

Depth to the Water Table

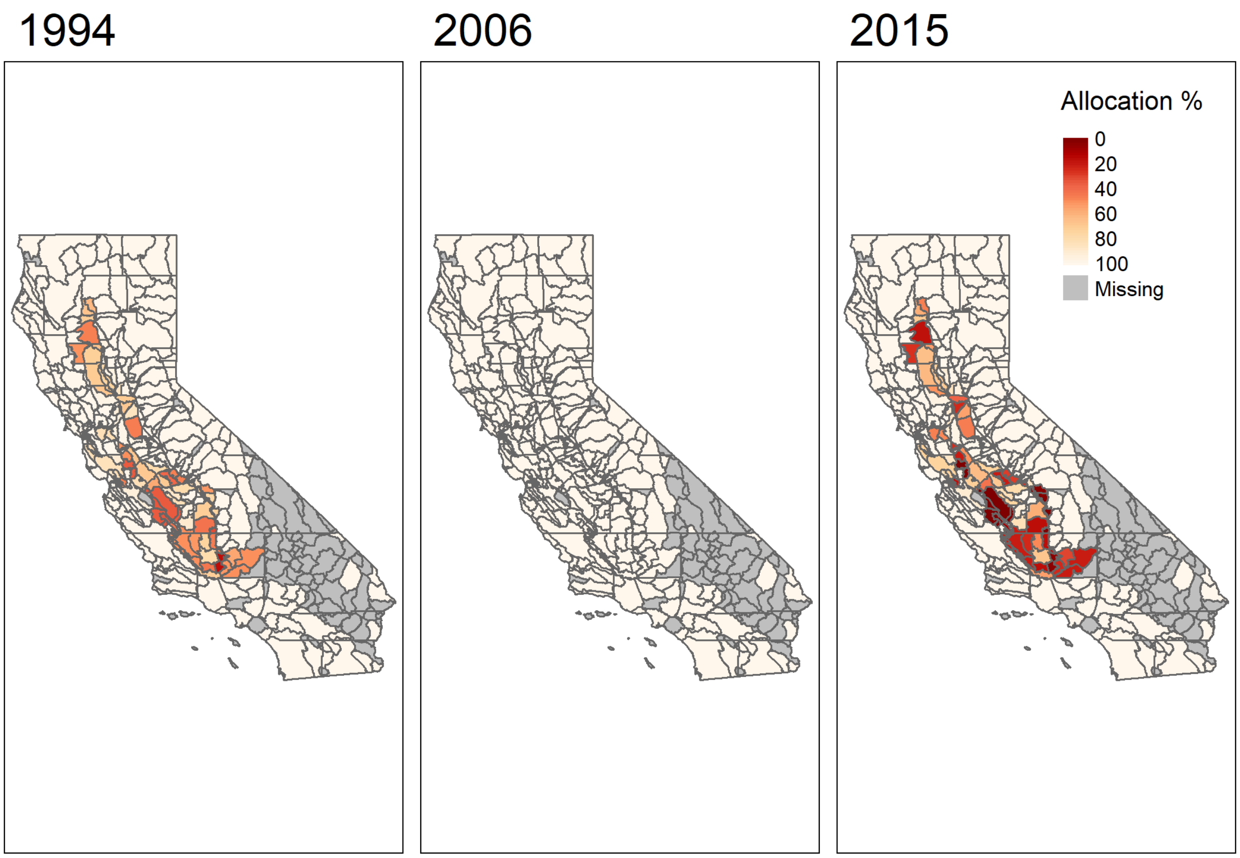
Monitor level measures of the depth to the water table are available from over 20,000 monitoring wells on average between 1993 and 2020. Depth to the water table measures come from two sources: the State Water Resources Control Board's Groundwater Information System and DWR's Periodic Groundwater Level Measurement.[14] 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-year groundwater depth), since the water table at that point in time 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.[15]

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 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.

[14] 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.

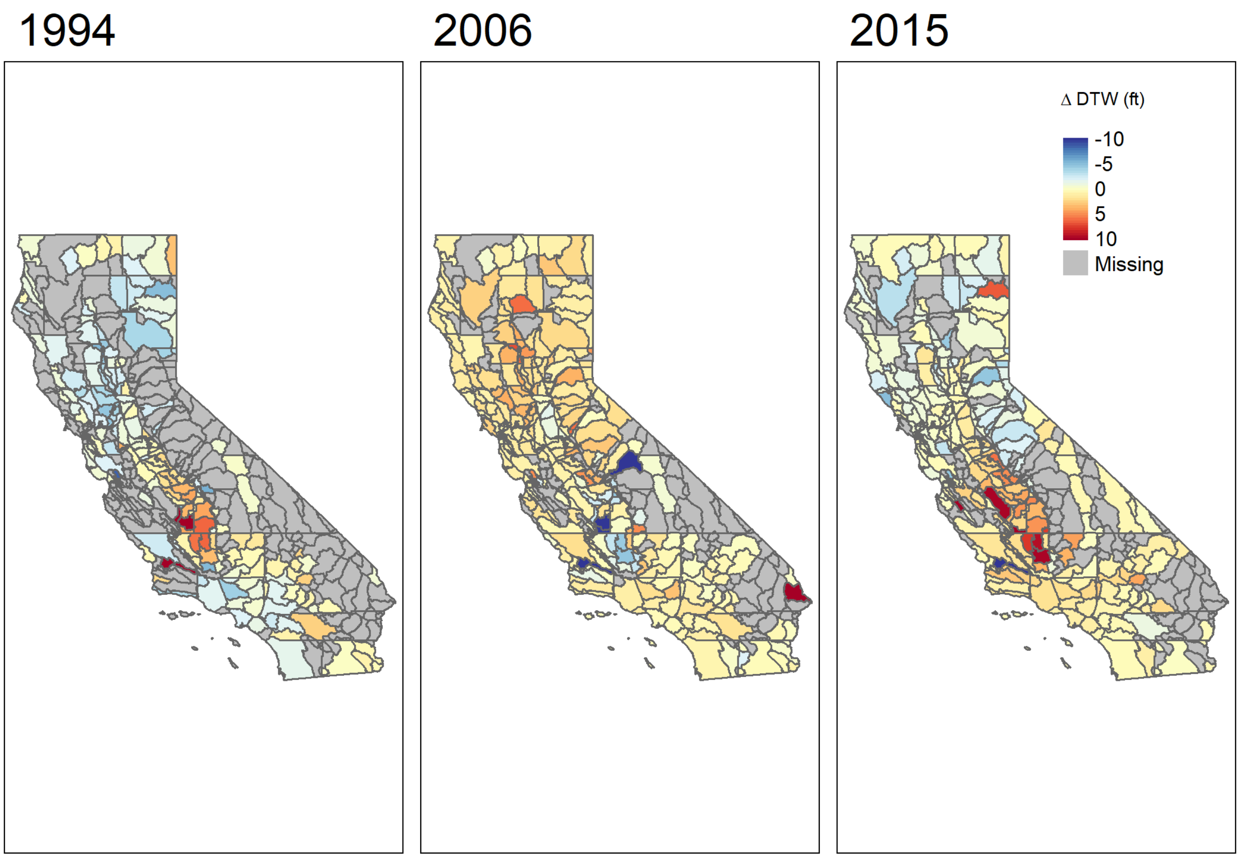
[15] To reduce the influence of extreme values, we exclude observations where a year-to-year change is more than 1.5 times greater than the inner decile range reported from all monitoring wells in the same DAUCO over our sample. This rule removes observations with drastically different changes in groundwater 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, but we cannot easily distinguish the source of error in these data.

Figure 2: Agricultural Surface Water Allocation Percentages



Note: 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 years like 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.

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 new well's location, the drilled well depth, intended use, and drilling date. These reports also contain a record of which wells were destroyed and their locations.[16] Our final outcome is the count of the total number of new agricultural irrigation wells per DAUCO-year. We also use the destruction records as an outcome in an alternative specification to test whether new well construction is offset by old well destruction.

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.

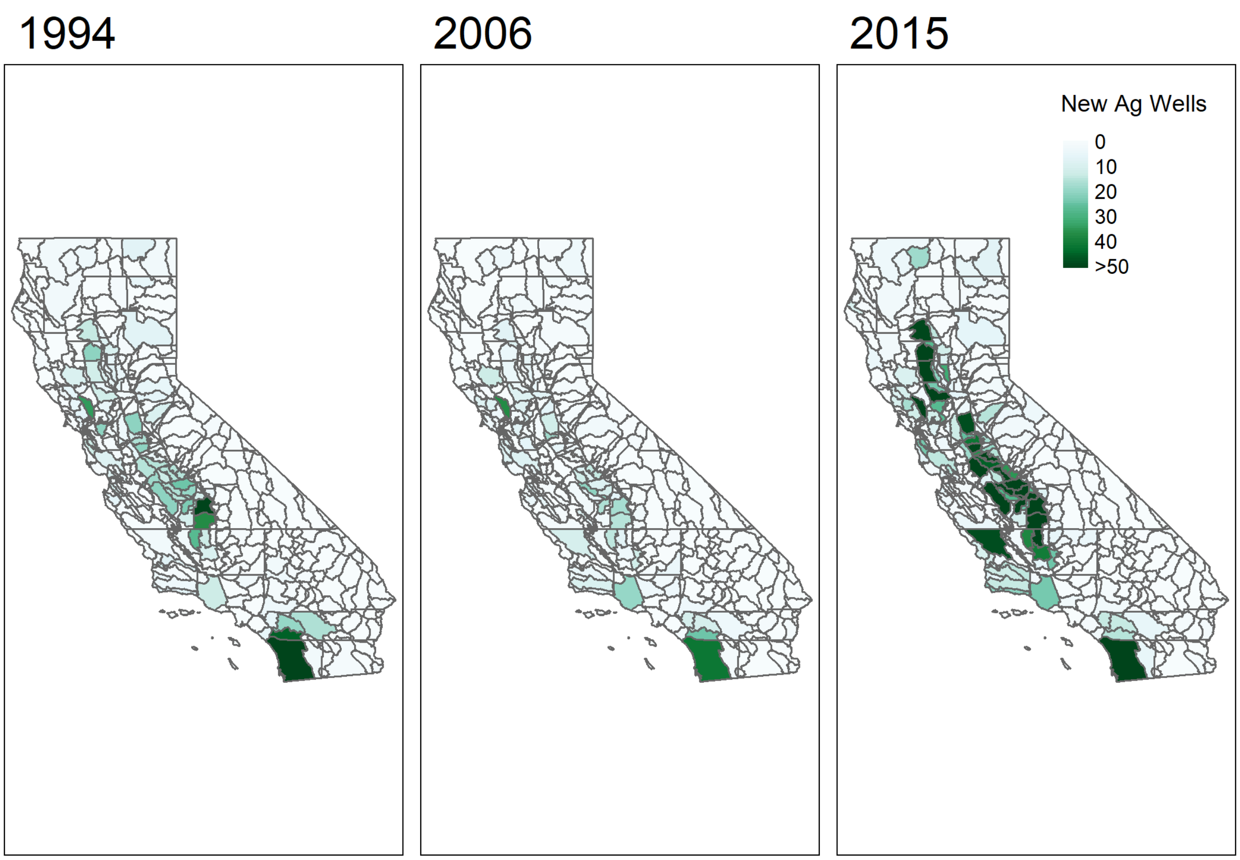
Well Failures

Panel data on domestic well failures at the well-year are available from 2014 to 2020. Beginning in 2014, DWR created a system for households to report domestic well failures. Reporting in this system is voluntary and is not linked to state-assistance or interventions (i.e. there are no known differential incentives for reporting in certain locations or years). 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.

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

[16] Since 1949, the California Water Code requires that well drillers complete a Well Completion Report with the California DWR within 60 days of the well construction and/or destruction. 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: 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.

Valley. They also occur disproportionately in locations that experience large agricultural surface water curtailments.

Weather

To measure extreme heat and precipitation we obtain weather observations from Schlenker and Roberts (2009) and PRISM climate data. The former, which are based on PRISM, provide daily temperature and precipitation data spanning 1993 to 2019 at a 2.5 km by 2.5 km grid. Given that our panel extends to 2020, we obtain daily temperature and precipitation from the PRISM data product, which measures these variables at a 4 km by 4 km resolution. For each day, we calculate the average temperature and collect information on total precipitation.

As is the convention with panel data studies on climate change, we the daily average temperature, T, to measure heat exposure and intensity over a calendar year in each grid using growing degree days and harmful degrees (Blanc and Schlenker, 2017),

$$GDD(T) = \begin{cases} 0 & \text{if } T \leq 8C \\ T-8 & \text{if } 8C < T \leq 32C \\ 24 & \text{if } T \geq 32C \end{cases} \tag{5}$$

$$HDD(T) = \begin{cases} 0 & \text{if } T \leq 32C \\ T-32 & \text{if } T > 32C \end{cases} \tag{6}$$

Precipitation is measured as local annual precipitation in millimeters. We sum GDDs, HDDs and precipitation over the calendar year to construct an annual measure of grid-level weather. To construct a DAUCO-level measure of weather, we take the average of all grids whose centroid is located in the DAUCO.

5 Empirical Model

Our empirical framework uses annual fluctuations in local weather and surface water 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,

$$\Delta DTW_{idt} = \beta_1 SWD_{dt} + \beta_2 HDD_{dt} + B' X_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt}. \tag{7}$$

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_{idt}. Specifying the outcome as a flow better matches the treatment variables and avoids the risk of spurious correlation from the non-stationary nature of the stock variable DTW_{idt}. The underlying parallel trends assumption is also more plausible for annual changes in groundwater depth. Trajectories of depletion vary across locations for many reasons, so it is unrealistic to think that groundwater depths across locations would move in parallel if exposed to the same values of the treatment variables. By differencing the outcome, we allow for differential trends in depths, or equivalently, level differences in the annual *pace* of depletion. We assume only that the pace of depletion across locations would follow parallel trends absent differences in environmental conditions.

Our two regressors of interest are SWD_{dt} and HDD_{dt}. SWD_{dt} measures surface water deliveries in AF 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_{dt} 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.

To obtain estimates that represent average effects for agricultural regions of California even though monitoring wells are not evenly distributed, we weight observations by the inverse number of monitoring wells in the DAUCO times the crop area of the DAUCO. Weighting by the inverse number of monitoring wells in the DAUCO moves from a dataset in which each well receives equal weight to one in which each DAUCO receives equal weight, and then weighting by DAUCO crop area moves to one in which each acre of crop land receives equal weight.

Instrumental Variables Model

Of the two treatment variables in Equation 7, HDD_{dt} is likely exogenous, conditional on well and year fixed effects and other measures of local weather. However, SWD_{dt} is not, since irrigation districts can influence their own surface water deliveries. For example, in a drought year, a district may purchase additional surface water, while its farmers also extract more groundwater in drought years. We therefore instrument for deliveries using surface water allocations, which are set ahead of the growing season based on environmental conditions and cannot be influenced by farmers or local officials. The exclusion restriction likely holds, since allocations are unlikely to be related to other determinants of local groundwater demand: Allocations are set based on precipitation conditions occurring in the mountainous regions during the rainy season, while groundwater demand occurs in agricultural valleys during the summertime. Still, to rule out a possible correlation between local weather and allocations, we include precipitation as a control variable in our full specifications.

Our preferred specification is the following model:

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

where the instrument SWA_{dt} measures surface water allocations in DAUCO d and year t. The first-stage relationship between allocations and surface water deliveries is strong, with an F-statistic that exceeds conventional thresholds (Table A1).

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 two-stage least squares:

$$\begin{aligned} Y_{idt} &= \beta_1 S\hat{W}D_{dt} + \beta_2 HDD_{dt} + B'X_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\ SWD_{dt} &= \gamma_1 SDA_{dt} + +\gamma_2 HDD_{dt} + \Gamma' X_{dt} + \lambda_t + \alpha_i + \mu_{idt}. \end{aligned} \tag{9}$$

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 (8), with the exception of α_i which denotes domestic well fixed effects. The coefficients 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

Farmers may mitigate the costs of heat and surface water curtailments through increased groundwater extraction on the intensive and extensive margins. For the extensive-margin response, we estimate the effect on the count of new agricultural wells constructed. For this outcome, we use Poisson regression, for which the feasible instrumental variables estimator is a control function approach estimated with Psuedo-Poisson Maximum Likelihood (PPML) (Wooldridge, 2015),

$$\begin{aligned} E[Y_{dt} | SWD_{dt}, HDD_{dt}, \mathbf{X}_{dt}, \alpha_d, \lambda_t] &= \exp\{\beta_1 S\hat{W}D_{dt} + \beta_2 HDD_{dt} + B'X_{dt} + \alpha_d + \lambda_t + \phi\hat{\mu}_{dt}\} \\ SWD_{dt} &= \gamma_1 SDA_{dt} + \gamma_2 HDD_{dt} + \Gamma' X_{dt} + \alpha_d + \lambda_t + \mu_{dt}. \end{aligned} \tag{10}$$

The dependent variable is the non-negative count of new agricultural wells in DAUCO d and year t. DAUCO fixed effects are captured by α_d; all other variables are defined as before. The regression is weighted by crop area in each DAUCO. Standard errors are clustered by DAUCO.

We use a Poisson model for this outcome because the parallel trends assumption is more plausible in proportions than in levels. Consider two DAUCOs that are identical except that one is twice as large as the other. A linear model would require the assumption that if two DAUCOs face identical conditions of surface water and heat, any other time-varying factor adds the same *number* of new wells to each DAUCO in that year. A Poisson model instead uses a more realistic "parallel trends in ratios" assumption: absent differences in the treatment variables, background movements in well construction would vary multiplicatively across DAUCOs rather than additively.[17] Poisson regression is also arguably more appropriate for non-negative count data, and it may be more efficient given the variable's right skew (see Figure A5 for a histogram). For robustness, we also report results using linear two-stage least squares.

6 Results

Damages: Groundwater Depletion and Well Failures

Table 2 reports results for the change in the groundwater depth from the two-way fixed effects and instrumental variables models described in equations (7) and (8). Columns (1) and (2) display the reduced-form effects of surface water allocations, without and with extreme heat and local weather controls. Columns (3) and (4) display results in which allocations serve as an instrument for surface water deliveries.

Our first main result is that surface water scarcity and extreme heat lead to groundwater depletion. Our preferred estimates in column (4) of Table 2 imply that a one AF/acre reduction in surface water deliveries leads to a 2.9 ft decline in the groundwater levels, holding extreme heat constant. Groundwater depth is responsive to extreme heat, with groundwater levels declining by 0.03 ft for every additional harmful degree day. Even holding water supplies constant, an increase in extreme heat will directly increase demand for water resources. The reduced-form effects reported in column (2) confirm the finding that surface water allocations have a negative and significant impact on changes in the depth to the water table.

To provide context for the magnitude of these estimates, we consider the heat and surface water scarcity experienced in 2021, a year that was especially hot and dry. In 2021, California crops received an average of 1.5 AF/acre of surface water (0.7 AF/acre below average) and experienced 120 HDD (23 HDD above average).[18] Our estimates suggest that the surface water curtailments

[17]This intuition is an informal generalization of the case of a binary variable and two periods, formalized by Wooldridge (2023) and further explained by Chen and Roth (2023). The precise assumption in that case is that the ratio of the expected values of the potential outcomes before and after treatment are equal between the treatment and control groups. A linear regression with a log-transformed outcome would allow us to use a similar assumption but is infeasible in our setting since the count of wells constructed can be zero. We also avoid "log-like" transformations such as $\log(x+1)$ or the inverse hyperbolic sine because their estimates are sensitive to units and do not correspond to a coherent estimand (Chen and Roth, 2023).

[18]For additional historical context on the size of typical shocks, we calculate the sample "within" standard deviation by computing the standard deviation of surface water and heat for each DAUCO across time, and taking the average

Table 2: Changes in Depth to the Groundwater

	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.

of 2021 resulted in a 2 ft decline in groundwater levels, and the extreme heat experienced in 2021 resulted in a 0.7 ft decline in groundwater levels.

Next, we show results for well failures in Table 3, which reports results from a two-way fixed effects linear probability model of domestic failures on heat and surface water scarcity. Columns (1) and (2) present reduced-form effects of surface water allocations, without and with local weather controls. Columns (3) and (4) display results in which allocations serve as an instrument for surface water deliveries. Given data constraints, the sample is restricted to self-reported well failures spanning 2015 to 2020, inclusive.

Our second main result is that extreme heat and surface water scarcity increase domestic

across DAUCOs. A one "within" standard deviation change is equal to 0.54 AF/acre for surface water and 14 HDD for extreme heat.

Table 3: Linear Probability of Reported Well Failure

	Reduced Form		IV		
	(1)	(2)	(3)	(4)	(5)
Ag SW Allocation (AF/acre)	-0.016	-0.028			
	(0.007)	(0.016)			
Ag SW Deliveries (AF/acre)			-0.030	-0.056	-0.062
			(0.010)	(0.019)	(0.016)
Harmful Degree Days		0.002		0.002	0.004
		(0.001)		(0.001)	(0.002)
Observations	468,339	468,081	468,325	468,067	106,726
N Groups	78,082	78,039	78,068	78,025	17,794
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓	✓
Other Weather		✓		✓	✓

Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. Column 5 reports results from the subset of counties within the California Partnership for the San Joaquin Valley. 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.

well failures, which compromise access to drinking water. Our preferred specification in column (4) indicates that an additional HDD increases the share of domestic wells that fail by 0.2 percentage points, and a one AF/acre reduction in surface water increases well failures by 5 percentage points. Translated to our 2021 example, well failure probability increased by 3.4 percentage points as a result of surface water curtailments and by 4.8 percentage points due to extreme heat. These estimates are large when compared to the sample mean probability of well failure of 3% displayed in Table 1.

We may overstate the impacts of weather shocks on access to drinking water if assistance for domestic failures increases or domestic well failures become more salient during droughts. This is a concern in our setting since support for domestic failures differs within the state, with 10 designated counties receiving differential treatment.[19] To test for this possibility, we restrict our sample to the 10 counties in the California Partnership for the San Joaquin Valley, and evaluate the effect of surface water and heat shocks on domestic well failures. Results in column 5 highlight that even within a sample of counties that receive similar state assistance, our results are unchanged.

We find that weather-driven well failures are concentrated almost exclusively in low-income populations and among communities of color. To investigate the distributional effects of well failures, we decompose the treatment effects reported in column (4) of Table 3 by estimating separate regressions that interact the outcome variable with subgroup indicators.[20] In Figure 5, panels (a) and (c) plot the effects for surface water curtailments and harmful degree days decomposed by income quartile, while panels (b) and (d) plot the effects decomposed by quartile of the non-white population share. Both treatment effects occur almost exclusively in relatively low-income and non-white communities. Relatively whiter communities exhibit almost no change in domestic well failures, and higher-income populations demonstrate only a small increase.

One Mechanism: Agricultural Well Construction

Our results so far establish that heat and surface water scarcity cause damages in the form of groundwater depletion and domestic well failures. Our goal now is to demonstrate that these damages are at least in part due to adaptation by agricultural producers. To do so, we estimate the effects of heat and surface water scarcity on the construction of new agricultural wells. Table 4 reports results from the count of new agricultural wells, where allocations are used as an instrument for surface water deliveries. Columns (1) and (2) present treatment effects from a linear specification, without and with extreme heat and local weather controls. Columns (3) and (4) display results from Pseudo-Poisson Maximum Likelihood estimation using a control function approach, again without and with weather variables. Table A4 provides the reduced-form results of well construction regressed directly on the allocations instrument.

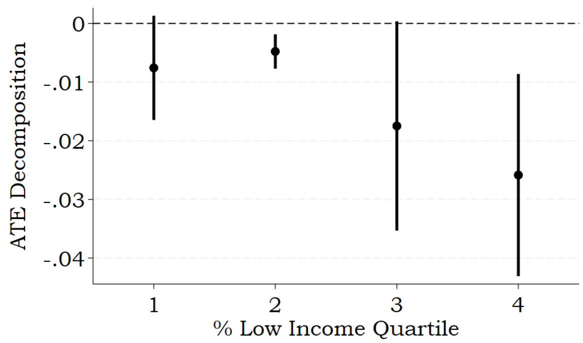
Our third main result is that heat and surface water scarcity induce farmers to construct more agricultural wells. Farmers drill approximately 46.2% more agricultural wells for a 1-AF/acre reduction in surface water and 1.3% more for every 1-HDD increase.[21] Assuming a uniform cost

[19]Information on dry well reporting, assistance and how it differs across regions can be found at:`https://mydrywell.water.ca.gov/report/shortage_resources`

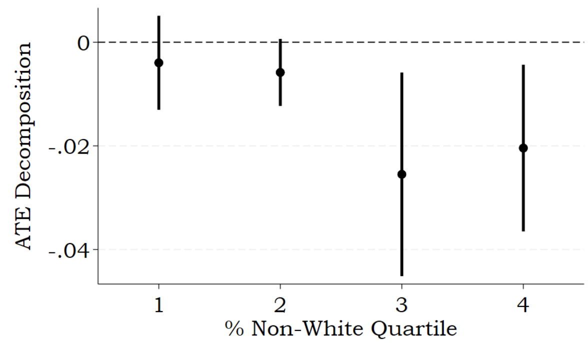
[20]These are not heterogeneous effects but rather a decomposition of incidence; for subgroups that are mutually exclusive and exhaustively defined, the coefficients across subgroups sum to the main coefficient in Table 3

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

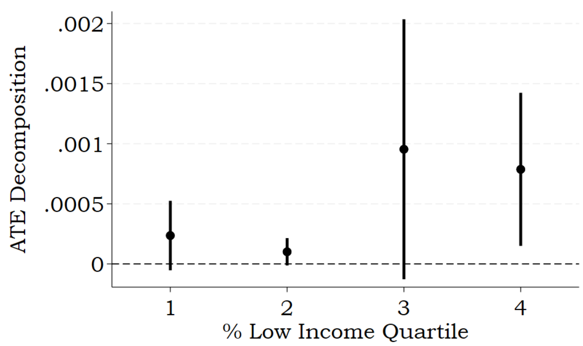
Figure 5: Decomposing Average Treatment Effects (ATE) by Local Demographics



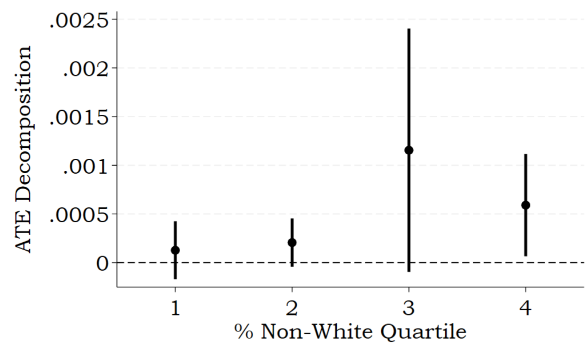
(a) Ag SW Deliveries (AF/acre)



(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 (i.e. treatment effects for the four groups sum to pooled treatment effect in Table 3). 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. In panels (b) and (d), the treatment effect is decomposed by quartiles of the 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.

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.

of $75,000 per well (California State Board of Equalization, 2023), our estimates imply that in response to the 2021 drought, farmers spent $24 million to construct 321 additional wells due to surface water curtailments and $22 million to construct 294 additional wells due to extreme heat. In addition to drilling more wells, it could be the case that farmers are responding by drilling deeper wells. Appendix Table A2 evaluates the effect of surface water and temperature shocks on the drilled depth of newly constructed wells. Wells appear to be drilled deeper in response to heat and water scarcity, though these estimates are imprecise.

One potential threat to interpreting these results as a mechanism of groundwater depletion is that the new wells constructed in response to weather shocks might not truly add to pre-existing irrigation capacity. Perhaps farmers construct new wells while at the same time retiring old wells, or perhaps they simply shift the construction of already-planned wells forward in time. Under either scenario, our main estimates would overstate the the extensive margin response. To investigate the possibility of well replacement, we estimate the effect of weather shocks on the count of agricultural well destruction. Results presented in Appendix Table A3 provide little evidence of well replacement. For surface water scarcity, the effects on well destruction are all much smaller than the effects on well construction. For extreme heat, if anything, the estimates suggest that well owners *delay* well destruction in response to heat exposure.

To investigate the possibility of intertemporal substitution, we augment our main specification to include three annual lags of surface water deliveries and harmful degree days. In Appendix Tables A6 and A7, we find no evidence that the lagged terms have opposite signs as the contemporaneous effects. Instead, if anything, the cumulative sums of the distributed lag coefficients are greater than the contemporaneous effects alone. In addition, the contemporaneous estimates are robust to the inclusion of lagged weather shocks. Taken together, our results imply that farmers respond to surface water scarcity and heat by expanding groundwater irrigation and on net constructing wells that otherwise would have not been drilled.

Decomposing the Mechanisms

Our main empirical estimates show that surface water scarcity and extreme heat cause both groundwater depletion and increased agricultural well construction. A natural next question is how much of the damages (in depletion, and by extension, domestic well failures) are explained by the mechanism of well construction. To answer this question, we apply the simple physical model from Equation (3) to decompose the effect on groundwater depth into three margins: (1) the extensive margin of well construction, (2) the intensive margin of increased pumping per well, which is unobserved, and (3) changes in recharge rates. We begin with a static version of the exercise and then move to a more realistic dynamic version.

Table A9 lists the parameter values we use for this exercise. They include (a) our point estimates on the change in groundwater depth and new well construction, (b) one parameter that we obtain directly from our raw data, the count of existing wells w, and (c) three parameters that we calibrate from the literature specific to California: average groundwater extraction per well (q), aquifer storativity (κ^{-1}), and the recharge rate ($\frac{\partial R}{\partial s}$). Where multiple published values are plausible, we choose conservative values that will reduce the size of the extensive margin relative to the other mechanisms.

To proceed, we substitute parameter values into Equation (3) and recover the unobserved intensive-margin response through algebra. We first convert our estimated effect on groundwater depth to the corresponding effect on the volume of groundwater stocks, by dividing it by κ. We obtain a 0.35 AF/acre decline in groundwater stocks per AF/acre reduction in surface water deliveries, net of recharge. Of this depletion, we attribute a maximum of 51% to a reduction in recharge (0.18 AF/acre, or a 1.5 ft decline), leaving a 0.17 AF/acre increase in gross groundwater extraction to be divided between the intensive and extensive margins. The extensive margin response is conservatively estimated to be 0.01 AF/acre, implying that 2% of the effect on groundwater stocks, or 5% of the effect on groundwater extraction, is attributable to new well construction. In this framework, the rest (0.16 AF/acre) must be due to the intensive margin: 46% of the effect on groundwater stocks, or 95% of the effect on groundwater extraction, is due to increased pumping from existing wells.

A problem with this static decomposition exercise is that it allows new wells constructed in a given year to only affect groundwater extraction in that year. Put differently, it attributes all groundwater consumption to either increased pumping from existing wells (the intensive margin) or new wells constructed in that year (the extensive margin)—but some of these existing wells may have been constructed recently, in response to earlier shocks. A full accounting of the extensive margin ought to include the effects of new wells on groundwater pumping in all periods, not just in the year of construction.

Decomposition with Dynamic Effects

We now extend our framework to allow new well construction to have persistent effects on groundwater extraction. Incorporating dynamics yields two changes to the conceptual framework. First, the target of decomposition changes from the contemporaneous effect of weather shocks on groundwater depth to the cumulative effect. Second, a new mechanism accounts for future groundwater extraction from new wells constructed in response to weather shocks today. The model is fully derived in Appendix Section A.1, and the result is Equation (11). The marginal effect of weather shocks on groundwater depth can now be decomposed into four mechanisms: (1) pumping more from each well (the contemporaneous intensive margin), (2) constructing new wells that pump more today (the contemporaneous extensive margin), (3) the future increase in pumping from new wells constructed today (the future extensive margin), and (4) recharge.

$$\underbrace{\frac{dDTW_T}{ds_t}}_{\text{cumulative effect}} = \kappa\Big[\underbrace{w_t(s_t)\times\frac{dq_t(s_t)}{ds_t}}_{\substack{\text{contemporaneous}\\ \text{intensive margin}}} + \underbrace{q_t(s_t)\times\frac{\partial w_t(s_t)}{\partial s_t}}_{\substack{\text{contemporaneous}\\ \text{extensive margin}}} + \underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau)\times\frac{\partial w_t(s_t)}{\partial s_t}}_{\text{future extensive margin}} - \underbrace{\frac{\partial R_t}{\partial s_t}}_{\text{recharge}}\Big]. \tag{11}$$

This equation is different from the static decomposition from equation (3) in two ways: The left-hand side is the cumulative effect on DTW_T rather than the contemporaneous effect DTW_t (capturing the cumulative change at some future point in time T from a surface water shock in the initial year t), and the "future extensive" margin term is new.

To calculate the decomposition empirically, we first estimate the cumulative effect using a distributed lag model. Then, of the four mechanisms in Equation (11), we already know three from the static decomposition above; only the future extensive margin is new. This term is challenging to estimate directly.[22] Instead, we back out the value of the future extensive margin from other terms we have already estimated. The intuition is that the future extensive margin is the only one of the four mechanisms that affects periods beyond the current one, so all lagged effects of weather shocks on groundwater depth can be attributed to it:

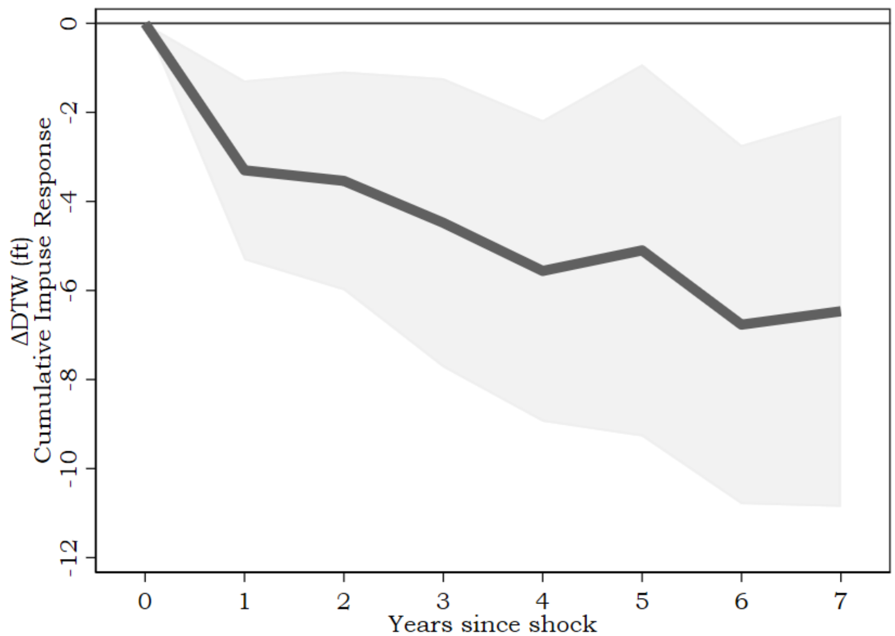
$$\frac{dDTW_T}{ds_t} - \frac{dDTW_t}{ds_t} = \kappa\Big[\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_t(s_t)}{\partial s_t}\Big] = \sum_{\tau=t+1}^{T} \frac{dDTW_\tau}{ds_t}. \tag{12}$$

To estimate the cumulative effect $\frac{dDTW_T}{ds_t}$, we need to choose a time horizon T for the distributed lag model. In principle, new wells built in response to surface water scarcity can affect groundwater depletion for many years after they are built. At the same time, we would expect their effects to decline over time, as water tables fall and older wells exit production. And in practice, every lag term we add to the regression costs us one year of data and identifying variation, reducing precision. As a compromise, we choose T by estimating a series of regressions that add lag terms in a stepwise fashion until the sum of their coefficients appears to plateau (i.e., until the last lag has a point estimate around zero).

Figure 6 plots the cumulative effect (i.e., the sum of contemporaneous and lagged coefficients) of a 1-AF/ac surface water shock on the depth to the water table in each of the seven years following the surface water curtailment. Just as in Table 2, the contemporaneous (year-1) effect of a 1-AF/acre reduction in surface water availability is a 2.9-foot increase in groundwater depth.

[22]This term requires knowledge of the entire time path of the average quantity pumped per new well q_τ every year into the indefinite future. It is therefore highly sensitive to assumptions about the lifespan of an agricultural well, as reflected in either the choice of time horizon T, or how quickly the pumping quantities fade to zero over time. In principle, we could read off q_τ from a statewide-representative well-level dataset of extraction and well age, but such data are not available. We could assume that wells have a finite average lifespan T and that they continue pumping the same value $q_\tau = q_t$ in each year until then, but the useful life of a well can vary widely. We also lack ideal data on wells that reduce or stop production, so the average amount pumped per well in future years becomes increasingly unreliable with greater τ.

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.

After that, effects of surface water shocks persist over time. The cumulative change in groundwater levels continues to grow over time, more than doubling to 6.7 feet six years after the initial shock. However, the impulse response flattens over time, and by year 7 there is no longer clear evidence that the cumulative change is continuing to grow. The pattern in this graph indicates that surface water scarcity (a) causes the greatest decline in groundwater stocks in the year in which it occurs, (b) continues contributing to groundwater depletion for several more years, which we attribute to the persistent effects of durable well construction, and (c) recedes to the baseline trajectory in less than a decade.

Based on this evidence, we choose a lag structure of $T = 6$ to estimate the cumulative effect of surface water shocks on groundwater levels. If surface water scarcity affects groundwater depletion for more than six years following the initial shock, we will understate the cumulative effect, but we find that regressions with more than seven lags are too noisy to be useful. We find that between the second and six years following a surface water shock, groundwater levels decline by an additional 3.9 feet. These lagged effects represent the difference between the cumulative and contemporaneous effects, so following Equation (12), we interpret this effect as the future extensive margin.

Including the dynamic effects of well construction, we estimate that the extensive margin (both contemporaneous and future) accounts for 75% of the effect of surface water scarcity on groundwater extraction. The cumulative effect of a one-year reduction in surface water of 1 AF/ac is a 0.81 AF/ac decline in groundwater stocks. Of this depletion, 22% is attributable to contemporaneous lost recharge, leaving a 0.63 AF/ac increase in groundwater extraction to be explained. The previously calculated contemporaneous intensive margin—increased pumping from existing wells—represents 20% of the decline in the water table, and 26% of the increase in extraction, resulting from surface water shocks. The remainder is attributable to the extensive margin: new well construction accounts for 58% of the decline in the water table and 75% of the increase in extraction resulting from surface water shocks.

These results show that new well construction plays a large role in how environmental shocks affect groundwater resources. The contrast between the static and dynamic versions of the decomposition shows that the durable nature of well construction gives rise to persistent effects that are important to take into account. The decomposition also demonstrates that out of the damages to groundwater levels and well failures we estimate as occurring in response to environmental shocks, a large fraction is indeed due to agricultural adaptation, through a mechanism that we can observe and estimate empirically.

7 Conclusion

Groundwater serves as a critical natural resource that must meet the needs of the environment, the agricultural industry, and millions of residential households in California. Using well-level data spanning almost three decades, this paper shows that climate change has accelerated groundwater depletion and exacerbated existing externalities. We demonstrate that this is driven in part by additional extraction by farmers as they rely more heavily on groundwater to mitigate surface water scarcity and extreme heat. This adaptation behavior limits the private costs of weather fluctuations to agricultural users in the near term, but imposes external costs on domestic well owners.

Importantly, these external 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 unregulated across the world. Myriad collective action governance, restrictions, and markets have been recently proposed or enacted as solutions to manage groundwater with some success (Ayres, Meng, and Plantinga, 2021; Burlig, Preonas, and Woerman, 2021; Earnhart and Hendricks, 2023; Bruno and Hagerty, 2023; Bruno, Jessoe, and Hanemann, 2024). Restrictions or moratoria on new well drilling, especially in drought years, are another potential regulatory instrument to curb groundwater depletion. Our work suggests that farmers respond to drought by drilling new wells and increasing pumping at existing wells, meaning groundwater externalities may persist through adjustments along both intensive and extensive margins. Effective policies will address both dimensions.

Our findings shed light on the extent to which adaptation will buffer the agricultural costs of climate change. A large body of 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 (Burke and Emerick, 2016; Auffhammer, 2018; Hultgren et al., 2022). Long-run costs may be reduced 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). But the open-access management of a common-pool resource may result in the opposite being true. We show that in the short-run, heat and surface water shocks 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; Perez-Quesada, Hendricks, and Steward, 2023).

Furthermore, this paper demonstrates that adaptive behaviors to shield against the damages of climate change may impose costs on other parties. While adaptation costs are conventionally included in 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 damages are not unintentionally imposing costs on others.

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For Online Publication: Appendix

A.1 Dynamic Effects of Well Drilling

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 empirically 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:

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

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

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

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

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

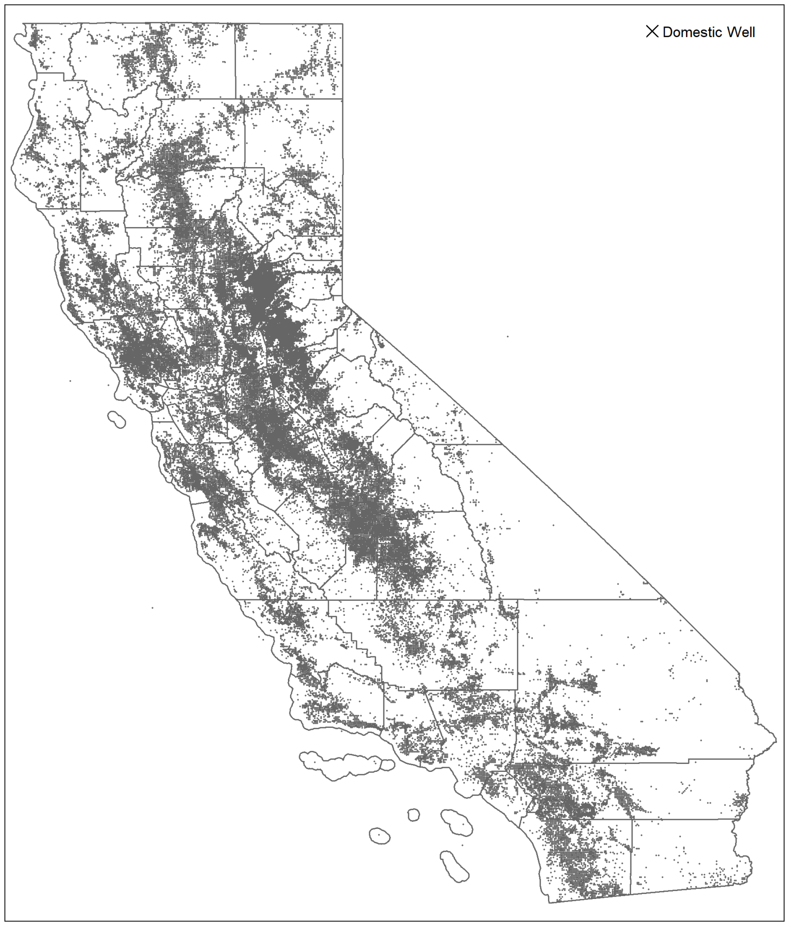
Then, assume a shock to surface water occurs in time t. The effect on future groundwater levels can be decomposed as:

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

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.

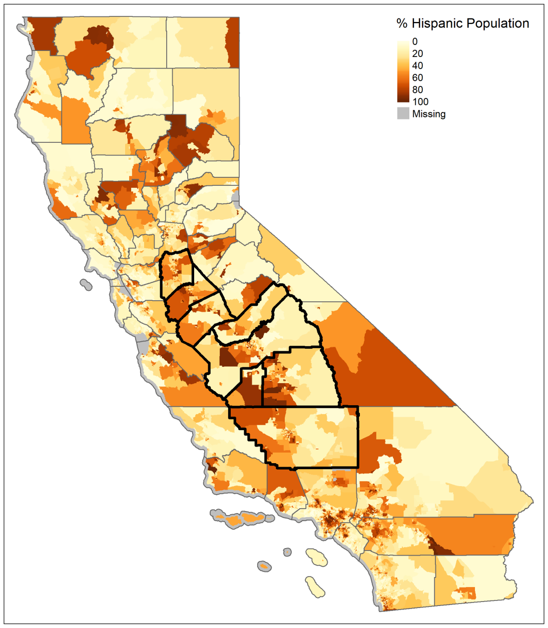
A.2 Supplementary Figures and Tables

Figure A1: Location of Domestic Wells



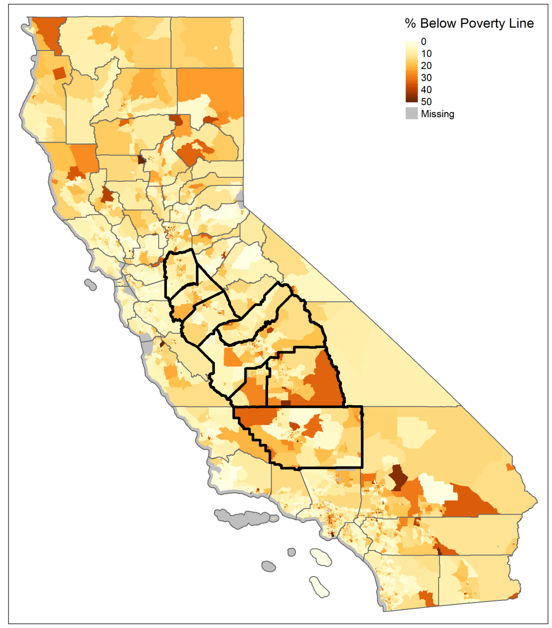
Note: Figure shows the location of domestic groundwater wells constructed. Data are from Well Completion Reports from DWR.

Figure A2: Population Demographics in California



% Hispanic Population

(a)

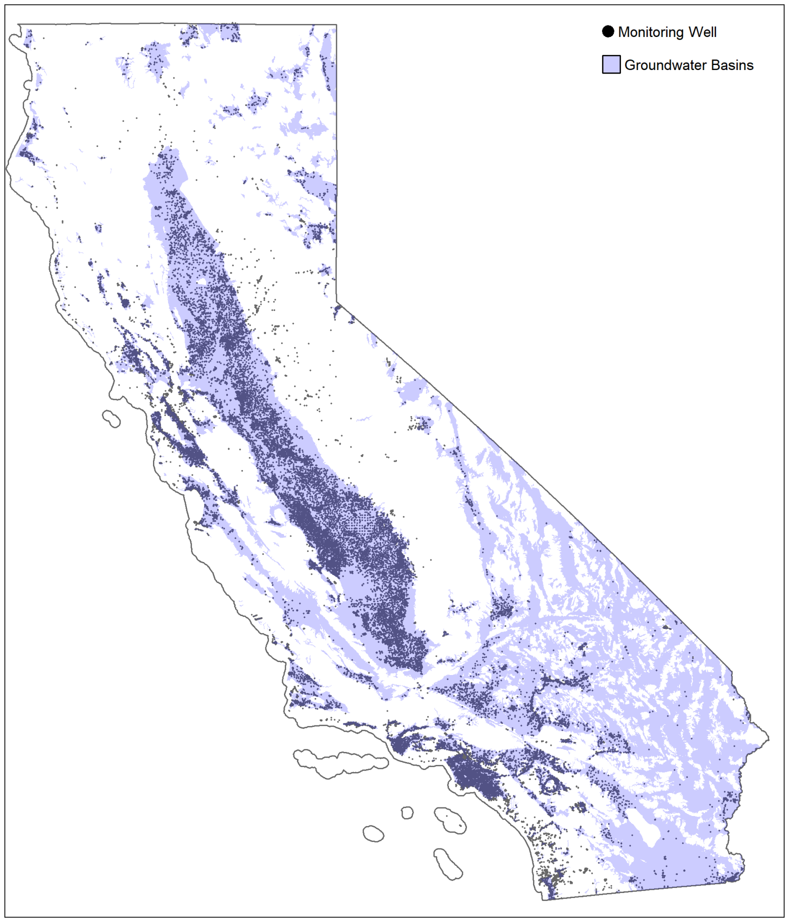


% Population below poverty line

(b)

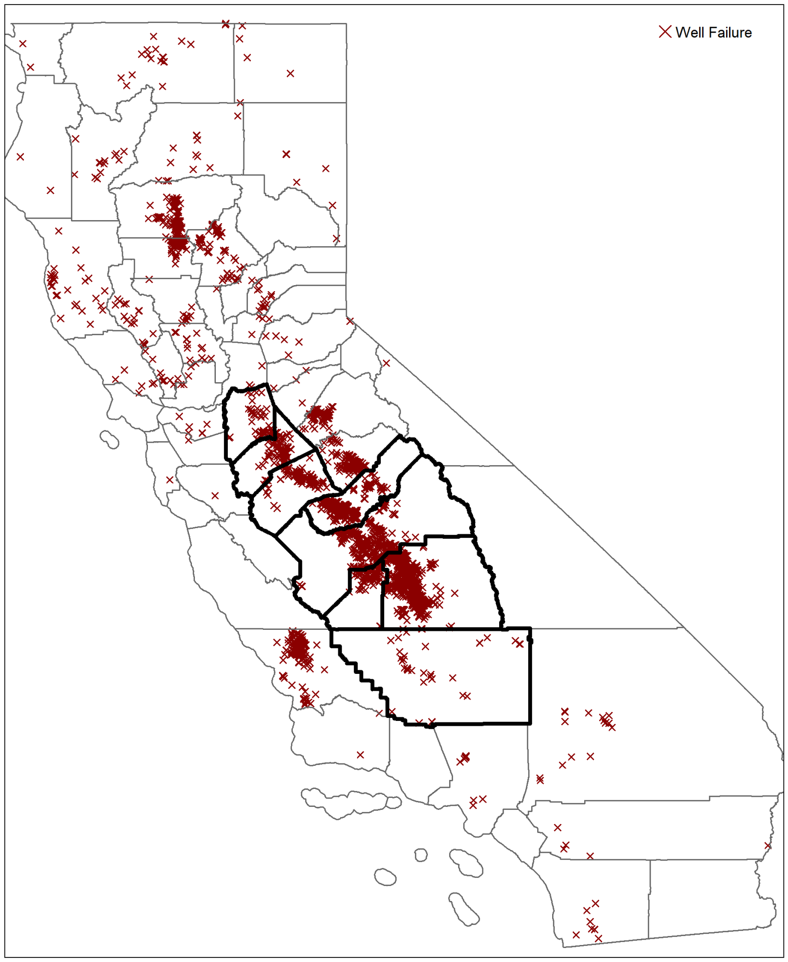
Note: Figure displays demographics at the Census tract level using data from 2020 (Manson et al., 2022). Panel (a) plots the percentage of the population that identifies as Hispanic. Panel (b) plots the percentage of households that fall below the federal poverty line for their household size. Bold county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

Figure A3: Location of Monitoring Wells in California Groundwater Basins



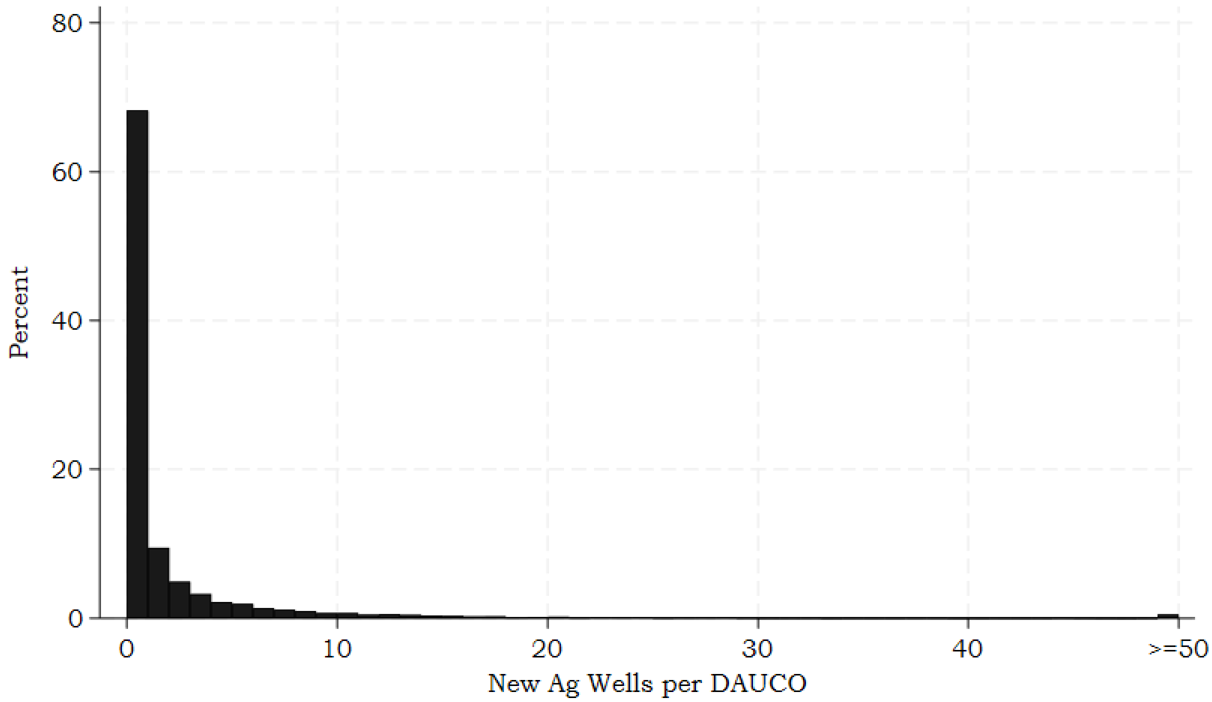
Note: Figure displays the locations of groundwater monitoring wells and California's principle groundwater basins. Each dot displays a unique groundwater monitoring well reported in our dataset. The blue shaded areas display the locations of Bulletin 118 groundwater basins in California.

Figure A4: Locations of Reported Well Failures, 2014-2020



Note: 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.

Figure A5: Histogram of Annual Agricultural Well Construction per DAUCO, 1993-2020



Note: Histogram plots the density of the count of agricultural wells constructed per year per DAUCO in our dataset. The bars show the skewed nature of the count data, with many zero observations, and small share of DAUCO-years with reported constructions exceeding 50 new wells.

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: 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.

Table A2: New Constructed Well Depth

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

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

Table A3: Destruction of Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation per crop acre (AF)	0.115	0.164	-0.0903	-0.00591
	(0.193)	(0.228)	(0.140)	(0.143)
Harmful Degree Days		-0.00215		-0.0228
		(0.00778)		(0.00814)
Observations	10,416	9,996	4,158	4,158
N Cluster	372	357	154	154
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 destroyed 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.

Table A4: 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.

Dynamic Empirical Estimation Results

Table A5 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 A6 and A7 consider the dynamics of agricultural well drilling. In Table A6, 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 A7 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 (10) 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 supports our main results reported in Table 4. 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 (10) 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 A5 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 A8. 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.

Table A5: 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.

Table A6: 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.

Table A7: 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.

Table A8: 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.

Table A9: Parameter Values for Decomposition

Parameter	Value	Units	Description
$\frac{dDTW}{ds}(s,h)$	-2.91	ft per AF/ac	Same-year gross change in DTW per AF/acre change in surface water. Results from Table 3 Column 4.
$\frac{dDTW_T}{ds_t}(s_t)$	-6.77	ft per AF/ac	Cumulative future change in DTW per AF/acre change in surface water. Results from figure 6
κ	8.33	unitless	Inverse storativity or specific yield Department of Water Resources (2020)
$\frac{\partial R}{\partial s}$	0.18	ft per AF/ac	Calculated from California DWR Water Balance Data, which reports regional values of recharge as a proportion of total applied water. We choose the maximum of a calculated range of 0.07 to 0.18 ft per AF/ac.
$\frac{\partial w}{\partial s}$	-4.60 $\times 10^{-5}$	wells/ac/yr per AF/ac	Change in the number of new agricultural wells drilled per year per crop acre due to a one AF/acre change in surface water. Results from Table 6 Column 4 multiplied by the total annual average of new agricultural wells divided by California crop acreage.
q	178	AF/well/yr	Average AF/year of groundwater pumped per well. Calculated from Department of Water Resources (2020) that estimates agriculture in California uses 15.2 million AF of groundwater per year divided by the total number of wells in our data.
w	8.60 $\times 10^{-3}$	wells/ac	Number of agricultural wells in use in California Well Completion Reports divided by the number of crop acres in California in our data.

Note: Table reports estimated and calculated values for parameters in the decomposition of intensive and extensive margin effects presented in equations (3) and (11). California Water Balance Data used to calculate recharge coefficient can be accessed at `https://data.cnra.ca.gov/dataset/water-plan-water-balance-data`

Additional Empirical Specifications

We conduct two falsification tests of our primary model. First, Table A10 reports results from a regression of 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 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 A11. 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 4 and A4 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

Table A10: 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.

Table A11: 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)
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.