

Externalities of Climate Adaptation in Common-Pool Groundwater Resources*

Jeffrey Hadacheck[†] Ellen M. Bruno[‡] Nick Hagerty[§] and Katrina Jessoe[¶]

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Abstract

Adaptation to environmental change can exacerbate existing externalities in common-pool natural resources. We document one such case: Farmers in California respond to heat and drought by extracting more groundwater, lowering the water table, and 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: low-income and Latino communities account for most of the effects on domestic well failures.

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[†]Department of Agricultural and Applied Economics, University of Wisconsin-Madison. Email: hadacheck@wisc.edu

[‡]Department of Agricultural and Resource Economics, University of California, Berkeley. Email: ebruno@berkeley.edu

[§]Department of Agricultural Economics and Economics, Montana State University. Email: nicholas.hagerty@montana.edu

[¶]Department of Agricultural and Resource Economics, University of California, Davis. Email: kkjessoe@ucdavis.edu

1 Introduction

Market failures attributable to the open-access management of common-property resources are widespread. Open-access management, which is common in resources such as fisheries, forests, and groundwater, is typically inefficient because each user acts without fully considering the costs of extraction to others (Hotelling, 1931; Gordon, 1954; Stavins, 2011; Hartman, 2018). A rich empirical literature confirms that open-access conditions lead to too much resource extraction at too quick a pace (Newell, Sanchirico, and Kerr, 2005; Costello, Gaines, and Lynham, 2008). But less clear is how these open-access externalities are affected by climate change (Taylor, 2023). These externalities may be exacerbated by adaptation choices: Natural resource stocks are often valuable for buffering weather shocks, so in open access, users may over-rely on them, exacerbating existing externalities. If so, environmental change can raise the value of sound resource management.

This paper empirically documents how agricultural water users respond to weather shocks, exacerbating existing market failures in groundwater resource management. Our context is California, the largest agricultural state in the U.S., where groundwater 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). The vast majority of this extraction is used for irrigation, and many areas that depend heavily on groundwater have experienced falling water levels, increasing pumping costs, and degraded water quality (Famiglietti et al., 2011; Pfeiffer and Lin, 2012; Merrill and Guilfoos, 2017; Department of Water Resources, 2020; Ayres, Meng, and Plantinga, 2021).

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.¹ 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, the shallowest domestic wells are also concentrated in disadvantaged communities comprised of low-income households and people of color.² Access to drinking water supplies among disadvantaged communities is a growing concern,

¹A spatial pumping cost externality occurs when localized cones of depression surrounding one well lower the groundwater table and increase pumping costs for nearby users when wells are closely spaced. The stock externality refers to the overall depletion of the resource, irrespective of well spacing, and makes groundwater more costly (or completely unavailable) the following year and beyond.

²California's San Joaquin Valley contains the majority of domestic wells in the state. It is a region that is over 50%

and the links between environmental conditions, agricultural groundwater extraction, and domestic well failures remain unclear (Pauloo et al., 2020).

Our overall thesis is that under open-access conditions, farmers in California respond to heat and drought in ways that exacerbate groundwater depletion, which worsens 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 in part to adaptation actions taken by agricultural producers: farmers also drill more new irrigation wells in response to heat and drought. We focus on well construction because data on groundwater extraction itself is unavailable.³ Finally, we use a simple conceptual model to argue that the remaining steps in the causal chain are mechanical. Using this model, we quantify the contribution of well construction to overall damages.

Our empirical approach uses year-to-year variation that differs across locations to identify the effects of contemporaneous and past 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. This empirical approach is similar to that of a shift-share instrument, in which the identifying variation comes from temporal shocks that differentially affect farmers across regions. Two-way fixed effects control for local fixed differences (such as historical water rights) and state-level shocks (such as recessions) that may affect both water access and producers' decisions.

Our research design measures the consequences of adaptation to transient shocks, not of adaptation to long-term shifts in environmental conditions.⁴ We make this choice because of the

Latina/o and contains some of the highest rates of poverty and food insecurity in the state.

³Ongoing work uses electricity consumption as a proxy to quantify the intensive-margin response attributable to weather shocks (Oehninger, Lawell, and Springborn, 2017; Hrozencik, Rouhi Rad, and Uz, 2023).

⁴In the framework of Lemoine (2023), the responses we study are primarily a combination of contemporaneous and ex-post adaptation to realized but unforecasted shocks in temperatures and surface water. Ex-post adaptation refers

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, 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 existing negative externalities.

Our first result is that contemporaneous 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 per acre 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 19% more than usual in the subsequent three years. Heat exposure equal to 2021 levels—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. A back-of-the-envelope calculation using the replacement costs of these dry wells suggests potential externalities of \$30.4 million from surface water shocks and \$34.3 million from excess heat of the magnitude experienced in 2021. Importantly, we find that the majority of domestic well failures occur in low-income communities and communities of color. Because well failures are known 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. Contemporaneous surface

to how farmers respond to past weather; whereas, ex-ante adaptation captures how farmers respond in anticipation of future weather based on forecasts.

water scarcity equivalent to the 2021 drought results in 321 additional new agricultural wells per year, a 32% increase in well construction relative to the usual pace. This additional agricultural well drilling costs California farmers roughly \$24 million in construction costs. Past surface water shocks also impact contemporaneous drilling decisions. The incorporation of three-year lags in surface water shocks increases new well construction from a 1 AF/acre reduction in surface water by 31%.

To understand the final links in the causal chain—how new well drilling affects groundwater depletion and drinking water—we would ideally estimate them directly. The challenge is that the data do not allow us to isolate the causal effects of new wells, because anything that drives well construction (including heat and drought) also tends to drive extraction at existing wells.⁵ Instead, we use a simple yet original conceptual model to demonstrate and quantify these mechanisms. The model 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. Combining our empirical estimates with known physical relationships, we estimate that 25% 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.

A central contribution of this work is to provide empirical evidence on how weather-driven agricultural groundwater depletion imposes external costs on drinking water users. To date, the literature on groundwater externalities has focused on quantifying the pumping and stock externalities imposed upon neighboring and future agricultural users (Provencher and Burt, 1993; Roseta-Palma, 2002; Brozović, Sunding, and Zilberman, 2010; Pfeiffer and Lin, 2012; Edwards, 2016; Merrill and Guilfoos, 2017). Less well understood are the acute and contemporaneous costs that groundwater pumping may exact on drinking water supplies in surrounding communities. Prior studies use hydrologic modeling approaches to forecast the impact of drought on well failures at local and regional scales (Gailey, Lund, and Medellín-Azuara, 2019; Pauloo et al., 2020). Our work builds on these studies by using data on observed well failures across a broad geography and a causal research design to empirically estimate the effects on domestic water users. Our framework also allows us to estimate the proportion of weather-driven agricultural groundwater

⁵That is, heat and drought cannot be used as an instrument for well construction, because they also affect outcomes through other mechanisms, violating the exclusion restriction. No other valid instrument is available.

depletion that is attributable to new well construction.

A second contribution is to bring empirical evidence to bear on how climate change is likely to exacerbate externalities under the open-access management of common-pool resources. The expansion of irrigation is a frequently discussed strategy for agriculture to adapt to warming temperatures and more variable water supplies (Rosenzweig and Parry, 1994; Mendelsohn and Dinar, 2003; Hornbeck and Keskin, 2014; Zaveri and Lobell, 2019). Recent empirical work has focused on the link between climate and agricultural demand for water, showing increases in irrigation as farmers seek to buffer against warming temperatures and more variable precipitation (Taraz, 2017). Less well understood is the extent to which climate change adaptation will affect existing groundwater extraction externalities (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. This carries implications for understanding the full costs of climate change, which must include the direct effects of weather shocks, the extent to which adaptation can reduce these damages (Barreca et al., 2016; Burke and Emerick, 2016), and the full social cost of adaptation (Carleton et al., 2022; Hultgren et al., 2022).

Finally, this paper 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., 2024). 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.⁶ Our work shows that adaptive behaviors under open-access management can exacerbate inequities when those with access to capital impose costs on disadvantaged groups.

⁶Recent work highlights the net benefits of markets relative to open-access management in the context of California groundwater (Ayres, Meng, and Plantinga, 2021).

2 Agriculture and Water in California

The context we study is California, a setting where agriculture accounts for 80% of consumptive water 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. 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.⁷ The state-operated State Water Project and federally run Central Valley Project

⁷Most 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. By custom or law, water is typically distributed uniformly to producers on a per-acre basis.

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. Figure C1 displays the differential entitlements to surface water across space by plotting the maximum entitlement each region of California can receive each year.

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 weather and environmental conditions in the mountains that occur in the preceding winter rainy season. Precipitation, usually in the form of snow, melts in the spring and then runs off into reservoirs where it is stored for summer irrigation in the Central Valley.⁸ There are 13 different contract types, where the allocation percentage a district receives differs based on the water project and fixed priority order. As a result, within a year different districts receive different allocation percentages, depending on the contract type and their appropriative water rights. Figure C2 plots the temporal variation in allocation percentages broken down by each of the 13 projects.

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, withdraw 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 dry periods, dependence on groundwater 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

⁸The regional weather conditions that matter for determining these allocations are distinct from the local weather conditions that may influence on-farm groundwater demand.

past 10 years groundwater levels in some SJV basins have experienced over a 100 foot reduction (Department of Water Resources, n.d.). Figure 1a plots the average annual groundwater depth across all wells that report at least 75% of the years in our panel. Between 1981 and 2020, the average depth to the groundwater across these wells has fallen from about 67 feet to over 92 feet. However, some regions have experienced larger declines than others. Figure 1b plots the long-run total depletion over the study period, averaged across wells within water regions. About 80% of locations experienced net depletion, with some areas in the lower Central Valley being depleted by as much as 100 feet (2.5 feet per year). Partly in response to these concerns, California passed historic groundwater regulation in 2014 – the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater by 2042.⁹

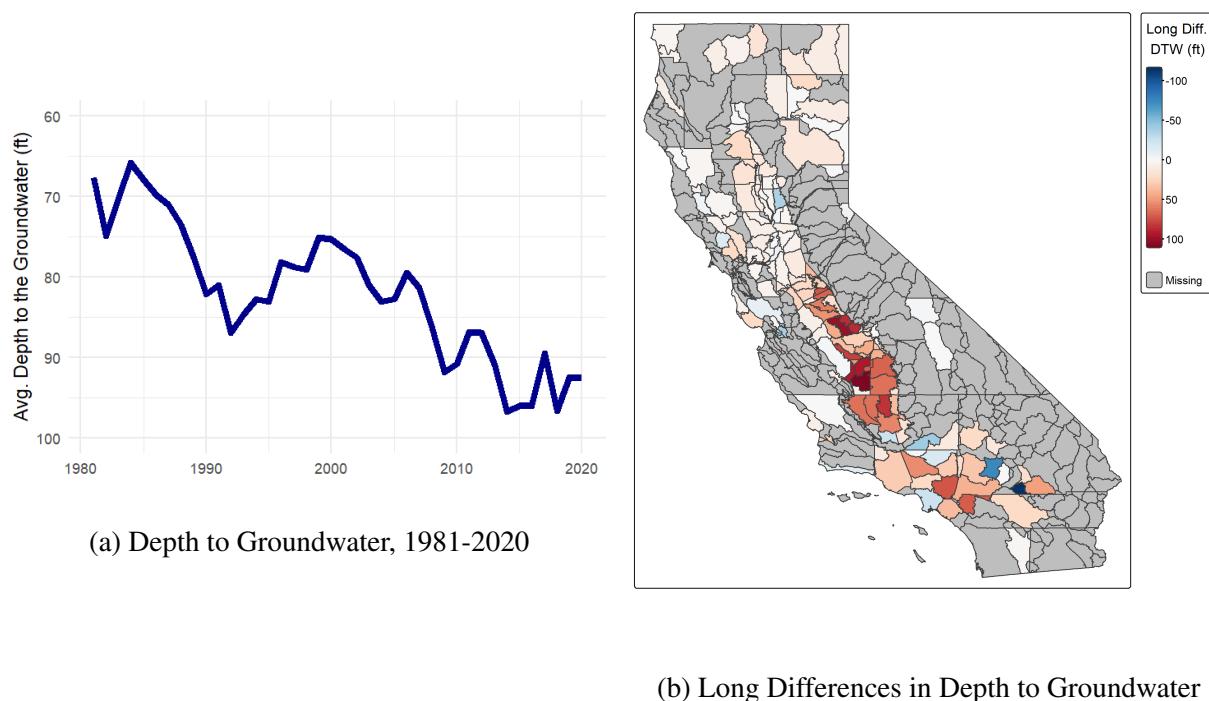
To increase groundwater irrigation on the intensive margin, a producer simply pumps more water from an existing well. The main variable cost is the electricity required to power the well; it scales roughly proportionally with both water quantity and depth. However, any single well exhibits declining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

To increase groundwater irrigation on the extensive margin, a producer drills a new well. He 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 and deep wells (California State Board of Equalization, 2023). The average depth of new agricultural wells has increased by over 200 feet since 1950 (Figure C3), reflecting the increasing investment that farmers are willing to make to secure groundwater access. Agricultural wells also are drilled with a wider diameter than residential wells to allow for higher flow rates. Their lifespan often exceeds 100 years. New wells are required to be reported to the state Department of Water Resources (DWR) and are typically constructed within a few weeks.¹⁰

⁹Most SGMA sustainability plans were developed and implemented by local groundwater sustainability agencies (GSAs) starting in 2022, after our sample of study. There are no direct restrictions on groundwater well drilling in these plans.

¹⁰After 2015, Well Completion Reports contain both permit dates and completed construction date. Using the subset of wells after 2015, Figure C4 plots the density of wells and the time between permit date and construction date. This figure supports that most wells are constructed and can actively pump water with little delay.

Figure 1: Groundwater Depletion in California, 1981-2020



Note: Figure displays the long-run depletion rates of groundwater in California. Panel (a) plots the average annual reported depth to groundwater among monitoring wells that report at least 75% of the years. Panel (b) maps the average change in groundwater levels within a region. The long difference is defined by the 3-year average groundwater depth at the end of the period (2018-2020) minus the 3-year average at the beginning (1981-1983) within each well. Well level changes are then averaged within a region and mapped in Panel (b).

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 domestic wells.¹¹ Private domestic well users draw groundwater from aquifers that are shared with agricultural users. In fact, the vast majority of irrigation wells are drilled within 2 km of a domestic well. 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.¹²

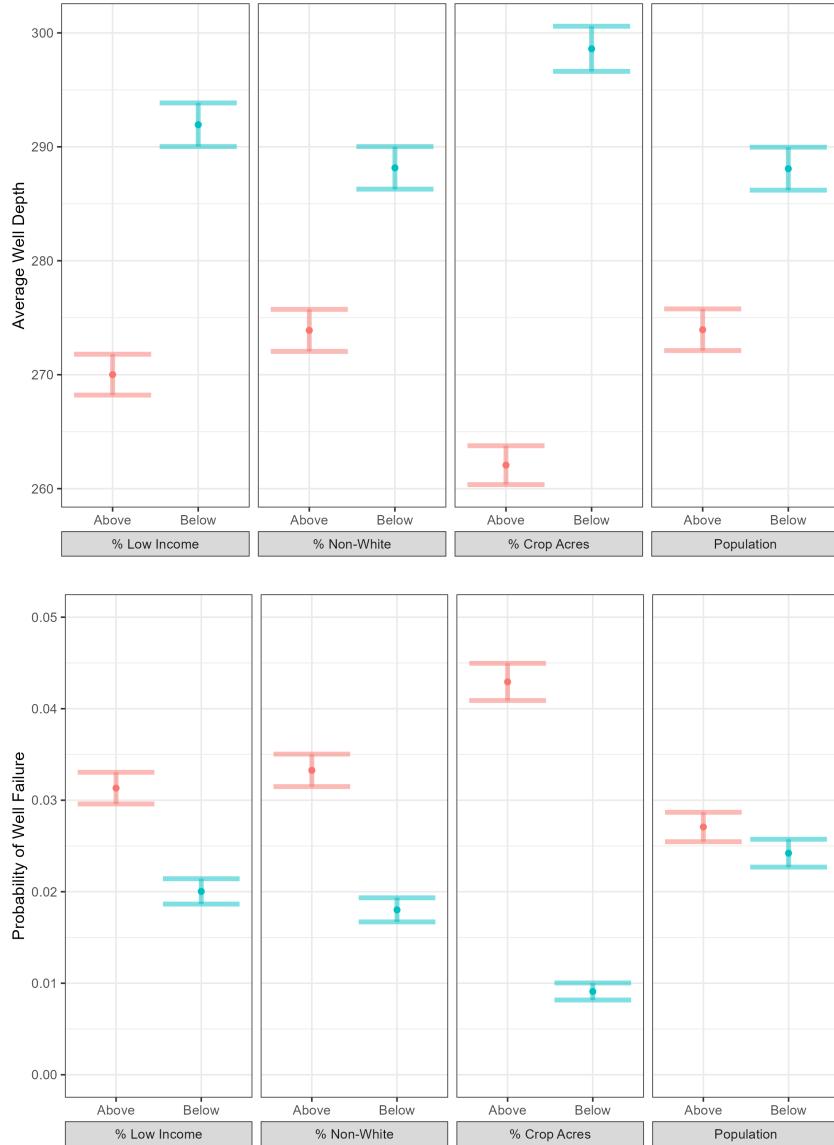
Private domestic wells are concentrated in agricultural regions of California and the San Joaquin Valley in particular (see Figure C5). These areas also comprise some of the most economically and socially vulnerable communities in California (see Figure C6). Populations in the San Joaquin Valley are 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%). Furthermore, households within the San Joaquin Valley that rely on private domestic wells tend to be more rural and have lower income than households connected to public water supply systems. Even within the domestic well-owning population, the study group of interest for this analysis, further disparities exist. Figure 2 illustrates that even among the domestic well-owning population, lower income, less white, and more agricultural communities tend to have domestic wells that are about 20 to 40 feet shallower on average. Shallower wells are the most vulnerable to well failures from declining groundwater levels. This figure also highlights that among domestic well users, private well failures are concentrated in relatively low income, rural and non-white communities.¹³

¹¹Community 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).

¹²Deteriorating 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.

¹³Shallower wells in these communities may be due to financial barriers or credit constraints, or alternatively higher groundwater tables. Well depth is one of several possible explanations for disparities in well failures, along with hydrogeological characteristics and nearby groundwater extraction, which could either be driven by more farmland or more intensive groundwater use. Section 6 empirically investigates the causes of weather-driven well failures.

Figure 2: Domestic Well Depth and Failure Probability by Local Demographics



Note: Figure displays the mean well depth (in feet) and 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 and agricultural measure. 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.

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 in the wintertime will shift the precipitation regime from snow to rain, reducing natural storage (mountain snowpack) and increasing dependence on built infrastructure (Siirila-Woodburn et al., 2021). Warming temperatures also increase crop demands for water during the summer growing season (Moyers et al., 2024). 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; Whitnall and Beatty, 2025). Historically, direct climate damages have been mitigated through adaptive behaviors by farmers (Burke and Emerick, 2016; Hagerty, 2021), including increased irrigation. These behaviors may explain why some earlier studies calculated minimal damages.

3 Conceptual Framework

We develop a conceptual framework based in physics and hydrology to clarify the relationships between farmers' responses to heat and surface water, groundwater levels, and access to drinking water. This framework will later inform an accounting exercise to quantify the intensive-margin response to heat and surface water shocks despite the lack of data on groundwater extraction. We start with a static set-up and then discuss a time element since these relationships have plausible dynamic relationships.

Following Provencher and Burt (1993) and Hotelling (1931), our framework recognizes that the absence of well-defined property rights generates open-access externalities. These can take the form of stock, spatial pumping cost, and/or water quality externalities (Brozović, Sunding, and

Zilberman, 2010; Pfeiffer and Lin, 2012; Peterson and Saak, 2018; Merrill and Guilfoos, 2017; Ayres, Meng, and Plantinga, 2021). The focus of our framework is not to quantify the magnitude (or relative importance) of these externalities, but instead to demonstrate how resource stocks and well failures respond to environmental shocks and to quantify the relative importance of well drilling in explaining this response.

Gross groundwater consumption for a representative farmer, denoted by C , is equal to 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 surface water (s) - a substitute for groundwater - and extreme heat (h):

$$C(s, h) = w(s, h) \times q(s, h) \quad (1)$$

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:

$$DTW(s, h) = DTW_0 + \kappa [C(s, h) - R(s, h)], \quad (2)$$

which depends on the starting depth to the water table DTW_0 , consumption, and recharge. The effect of one unit of consumption and recharge 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 .¹⁴

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:

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

¹⁴ κ represents the inverse of storativity, a physical property of an aquifer. 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. 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 sediment.

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.¹⁵

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:

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

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 empirically back out the intensive-margin effect, even though groundwater extraction is not directly observable, because we observe or estimate the other terms.

Which margin(s) should we expect to dominate? All three likely have important roles. First, the intensive margin is likely to be larger than the extensive margin due to the high fixed costs of constructing a new well. Second, the extensive margin is also likely to be present, because new wells are the only way to increase groundwater extraction when existing wells reach their maximum flow rate or when they fail. The extensive margin therefore can be expected to be larger when fixed costs are lower relative to variable costs and where the pace of depletion is greater. Third, the recharge effect is mechanical and will always be present: some fraction of the surface water that is delivered and applied to fields percolates into the aquifer, depending on irrigation technology, climate, soil, hydrology, and geology. Recharge is therefore larger in relative terms when the other two effects are smaller in absolute terms, which will occur when groundwater consumption is more expensive (i.e., when water levels are deeper, energy costs are higher, and well yields are higher).

¹⁵For a heat shock, recharge also falls because heat increases evaporation, meaning that less of the applied water makes its way into the aquifer.

Dynamics

Given that groundwater wells require upfront costs to drill and have a long lifespan, the decision to drill a well and the consequences of that decision are dynamic. One approach to characterizing this decision is to model well drilling as a forward-looking investment in which drilling decisions depend on current weather realizations and farmer expectations about future groundwater stocks, surface water supplies, and weather. The optimal drilling decision also depends on the existing stock of wells and the option value of this well. Estimating how well drilling responds to beliefs about the future climate would require exogenous variation in those beliefs, which is difficult to find. We focus instead on a narrower question: how well drilling responds to contemporaneous and recent shocks to environmental conditions.

Our goal is not to fully characterize the well drilling choice or how it responds to climate and groundwater depletion. Instead, we seek to show qualitatively that well drilling does respond to environmental shocks and that it is a quantitatively important mechanism for the effects of these shocks on groundwater depletion. Although well drilling is likely driven *more* by expected future conditions, temporary shocks are also important in our setting. First, relative to other agricultural investments, well construction costs are low. The cost of drilling a well is less than 15% of the establishment cost of a typical almond orchard in the Northern San Joaquin Valley (Goodrich et al., 2024). Second, well drilling offers a short-run option to buffer high-value perennial crops in California from within-year surface water scarcity and heat. Third, temporary shocks may carry information about the future climate.

In Appendix A, we incorporate some dynamics into the decomposition above. We expand equations (1-3) to allow for lagged effects of both weather on well drilling and of well drilling on groundwater levels. The dynamic decomposition yields two additional margins of response to a given weather shock. The first dynamic response, future groundwater consumption from wells constructed in response to contemporaneous shocks, may occur because the marginal cost of groundwater extraction is relatively low after the fixed cost is incurred. Therefore, total extraction may remain elevated in future years from the weather-driven increase in the inventory of wells.

The second dynamic response, contemporaneous well drilling decisions from past weather shocks, may be positive or negative. On the one hand, past drought and heat can update farmers' beliefs about future weather, which may induce farmers to drill more wells beyond just the initial year transitory shocks are realized. On the other hand, well drilling may simply be shifted forward in time (i.e., intertemporal substitution), which implies that past drought and heat may lead to *fewer*

Table 1: Summary Statistics

	Unit	Count	Mean	SD	Min	Max
<i>Outcomes:</i>						
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 (ft)	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
<i>Independent Variables:</i>						
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).

wells drilled in the contemporaneous year.

Given the possibility of these dynamic responses, our empirical analysis allows for both phenomena and estimates their magnitude and significance. This extension of the static framework still does not incorporate forward-looking choices; instead its purpose is to provide a more complete accounting framework for quantifying the margins by which weather shocks affect groundwater availability.

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.

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 1993-2020.¹⁶ 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.¹⁷ 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.¹⁸

Figure 3 displays the variation in surface water allocations across the 390 DAUCOs in three 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 low levels of precipitation and snow melt near each project’s reservoirs in the Sierra Nevada Mountains. 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.¹⁹ Within each monitor-year, we select a single date to measure the depth to the water table. Following DWR conventions, we choose the reading closest to March 15 of the subsequent year (e.g. March 15, 2016 to measure the 2015 end-of-year

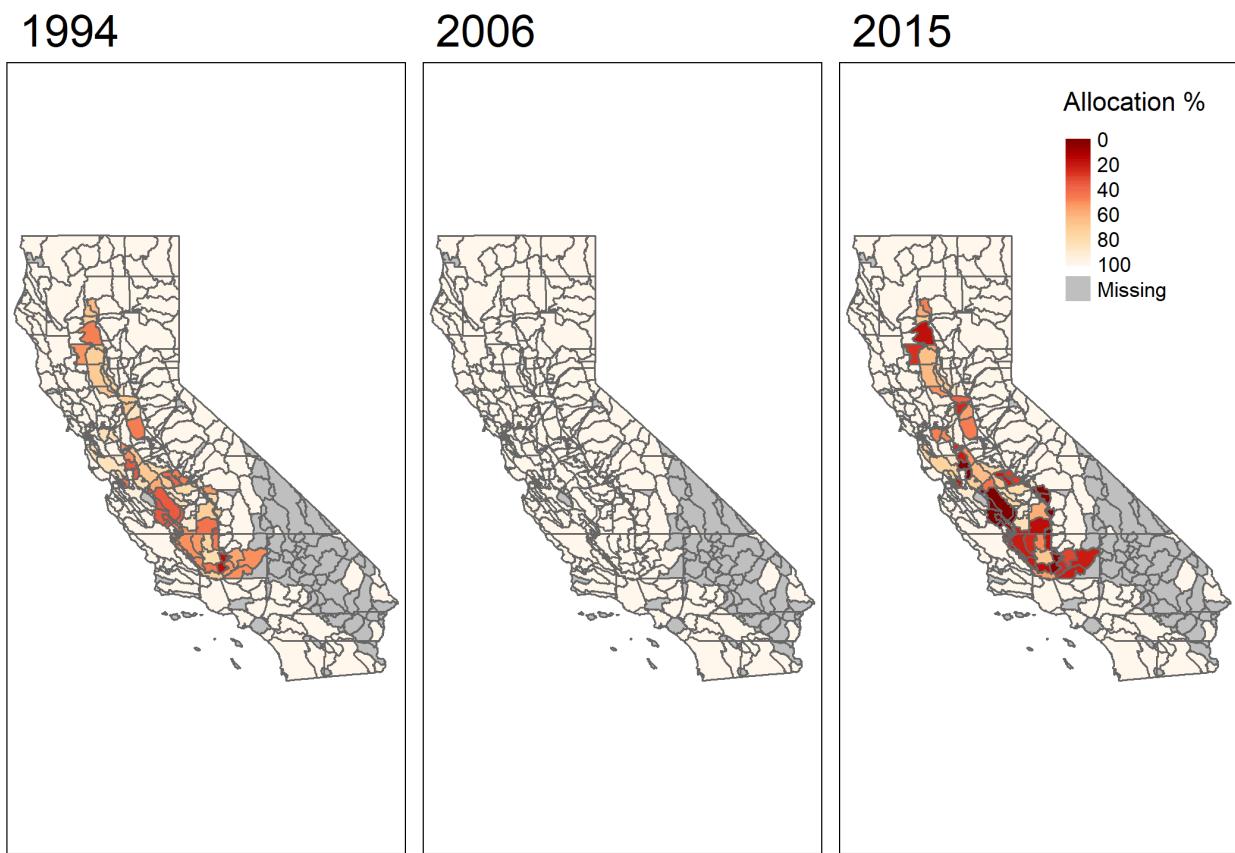
¹⁶Surface water delivery data for the CVP are first available from the U.S. Bureau of Reclamation in a digitized format in 1993. Therefore, these variables determine the temporal length of our final panel for analysis.

¹⁷DWR uses DAUs to subdivide the state’s hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis. For this study, we use static boundaries of DAUCOs at their 2018 definitions.

¹⁸We 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.

¹⁹Figure C7 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.

Figure 3: Agricultural Surface Water Allocation Percentages



Note: Figure graphs the fraction of agricultural water entitlements to be received by irrigation districts across 390 DAUCOs 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.

groundwater depth).²⁰ Year-to-year differences in monitor-level depth measure the change in the depth to the water table.²¹

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 4 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.

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.²² 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.

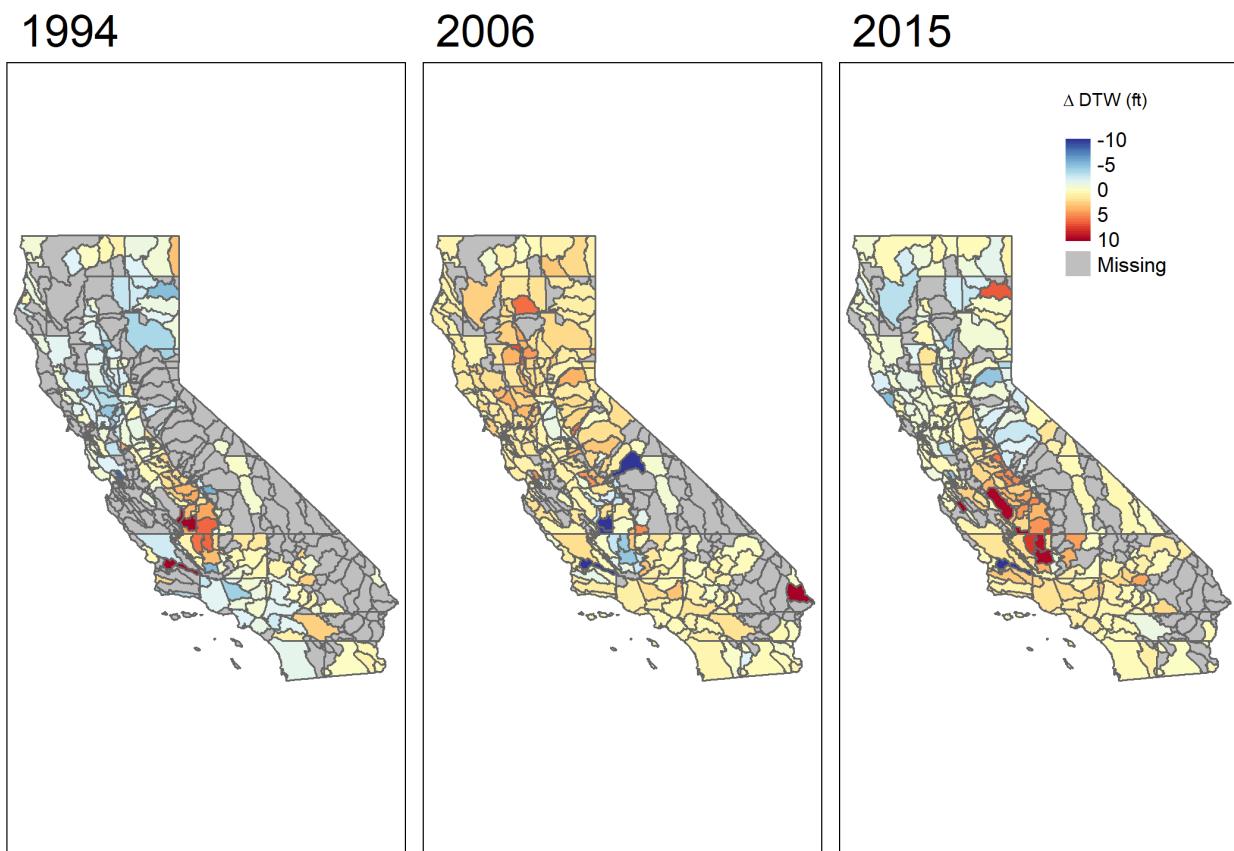
Figure 5 maps new agricultural well construction for the years 1994, 2006, and 2015. New well construction varies from year-to-year and increases in drought years. This activity is also concentrated in the San Joaquin Valley. A visual comparison of Figures 3 and 5 suggests that well construction is more pronounced in location-years that experience the largest surface water curtailments.

²⁰DWR measures spring groundwater levels this way because mid-March is the time when groundwater levels are typically at their annual maximum – it falls after most of the year's precipitation and before the irrigation-intensive growing season (Department of Water Resources, 2021). It is also a common time of year for the California Department of Natural Resources to collect groundwater measurements.

²¹To 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.

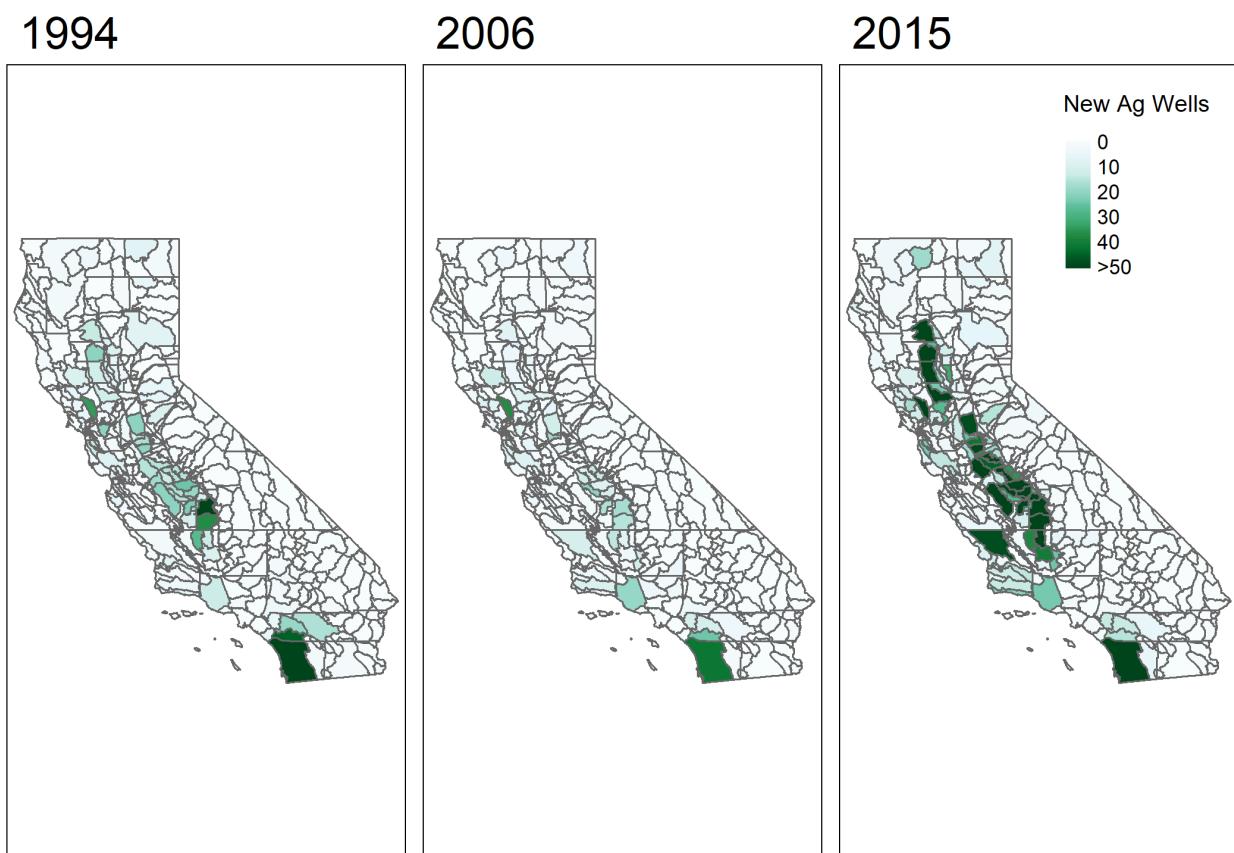
²²Since 1949, the California Water Code requires that well drillers complete a Well Completion Report with the California DWR within 60 days of the well construction and/or destruction. Prior to 2015, all Well Completion Reports were handwritten and later digitized for the construction of this dataset.

Figure 4: Annual Changes in Depth to the Water Table (ft)



Note: Figure displays the average changes in depth to the water table (ft) 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.

Figure 5: 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.

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 there are no known differential incentives for reporting in certain locations or years. These data, shown on a map in Figure C8, 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 over an approach that estimates failures based on the relationship between well depth and groundwater table height, which risks misclassifying wells for other reasons; for example, because they have been retired or because gaps in monitoring data lead to prediction errors (Gailey, Lund, and Medellín-Azuara, 2019).

Since 2014, over 4,000 domestic well failures have been reported. The black outlined region of Figure C8 illustrates that these well failures are concentrated in California's San Joaquin Valley. They also occur disproportionately in locations that experience large agricultural surface water curtailments. The persistent lowering of groundwater levels as shown in Figure 1a makes it difficult for domestic wells to recover. In our raw data, only two reported well failures are repeated failures across years.

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.

To measure the impact of temperature, we follow the convention in the agronomy and climate change economics literature of converting daily mean temperature, T , into growing degree

days (GDD) and harmful degree days (HDD) (Blanc and Schlenker, 2017).²³ Based on climate change studies in California that define the bounds for growing degree days and threshold for harmful degree days (Schlenker, Hanemann, and Fisher, 2007), we use the formulas below to convert daily temperatures into GDDs and HDDs,

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

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

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.

²³Our measure of growing degree days comes from agricultural experiments demonstrating that below (and above) certain thresholds, plants cannot absorb (additional) heat, while within these bounds heat absorption increases linearly with temperature. Our measure of harmful degree days stems from research showing that temperatures above the threshold are harmful for agricultural yields (Herrero and Johnson, 1980; Wilson and Barnett, 1983; Schlenker and Roberts, 2009).

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,

$$\Delta DTW_{idt} = \beta_1 SWD_{dt} + \beta_2 HDD_{dt} + \beta_3 GDD_{dt} + \beta_4 P_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt}. \quad (7)$$

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 . We choose to focus on extreme heat since warmer temperatures are projected to increase evaporative demand and reduce soil moisture, leading farmers to demand more water (Arias et al., 2021; Albano et al., 2022). We also control for annual growing degree days GDD_{dt} and total precipitation P_{dt} . 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 monitoring well receives equal weight to one in which each DAUCO receives equal weight. Then, weighting by DAUCO crop area moves to one in which each acre of crop land receives equal weight. This weighting provides point estimates that are representative of the target population, the average

agricultural water user.

To incorporate dynamics, we expand the static specification to allow contemporaneous and past surface water shocks and heat to impact changes in groundwater levels,

$$\begin{aligned}\Delta DTW_{idt} = & \sum_{\tau=0}^b \beta_{1\tau} SWD_{dt-\tau} + \sum_{\tau=0}^b \beta_{2\tau} HDD_{dt-\tau} + \\ & \sum_{\tau=0}^b \beta_{3\tau} GDD_{dt-\tau} + \sum_{\tau=0}^b \beta_{4\tau} P_{dt-\tau} + \lambda_t + \alpha_i + \varepsilon_{idt}.\end{aligned}\tag{8}$$

All variables are defined as in equation (7), except our regressors of interest are now given by the vectors $SWD_{dt-\tau}$ and $HDD_{dt-\tau}$. These vectors capture contemporaneous and lagged surface water deliveries and harmful degree days, respectively. The time horizon for the distributed lag is defined over $\tau = [0, b]$, where $\tau = 0$ corresponds to contemporaneous shocks and b denotes the number of annual lags in the model. This specification tests for contemporaneous, β_{10} and β_{20} , and persistent effects, $\beta_{1\tau}$ and $\beta_{2\tau}$ when $\tau \in \{1, b\}$, of environmental shocks. The cumulative effects of surface water and heat shocks on groundwater levels over time horizon b are given by $\sum_{\tau=0}^b \beta_{1\tau}$ and $\sum_{\tau=0}^b \beta_{2\tau}$.

Instrumental Variables Model

SWD_{dt} may suffer from selection bias, 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. To address this concern, we instrument for deliveries using surface water allocations.²⁴ Surface water allocations are the product of a district's time-invariant maximum entitlement and a time-varying allocation percentage. This variable is similar to a shift-share instrument, interacting cross-sectional variation in maximum surface water supplies (shares) with temporal variation in overall water availability (shifts). But it contains richer identifying variation than a simple shift-share instrument, because the shifts (i.e., the allocation percentages) themselves vary across regions and contract types.

Our initial specification is the following model:

$$\begin{aligned}\Delta DTW_{idt} = & \beta_1 \hat{SWD}_{dt} + \beta_2 HDD_{dt} + \beta_3 GDD_{dt} + \beta_4 P_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\ SWD_{dt} = & \gamma_1 SWA_{dt} + \gamma_2 HDD_{dt} + \gamma_3 GDD_{dt} + \gamma_4 P_{dt} + \lambda_t + \alpha_i + \mu_{idt},\end{aligned}\tag{9}$$

²⁴Conditional on well and year fixed effects, local weather is likely exogenous.

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 F-statistics (≥ 90) that exceed conventional thresholds (Table C1).

The identification assumption (i.e., the exclusion restriction) is that surface water deliveries are the only channel through which surface water allocations – specifically, their variation over time at a given location, which are driven by the allocation percentages – are related to groundwater depletion and our other outcomes. This assumption is likely to hold for three reasons. First, allocation percentages are administrative calculations used only to determine surface water deliveries; there are no other channels through which allocations per se would affect groundwater. Second, reverse causality is unlikely, as allocations are not influenced by demand-related factors but rather set ahead of the growing season according to environmental conditions. Allocation percentages are engineering assessments of the amount of water that is physically and legally available to be delivered that year, based on reservoir storage, precipitation, and mountain snowpack (USBR, 2017; DWR, 2025).²⁵ Third, the weather reflected in surface water allocations is separated both spatially and temporally from the weather that directly influences local groundwater demand: Allocations are determined by precipitation in mountainous regions during the winter rainy season, while groundwater demand is driven by conditions in agricultural valleys during the summer growing season. For these reasons, water allocations should not depend on local weather conditions. To test for the possibility that local weather impacts surface water allocations, we regress annual surface allocations on local weather. Results which are reported in column (4) of Table C1 indicate that local weather conditions are not key determinants of surface water allocations (or deliveries).

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 again estimate an in-

²⁵For the Central Valley Project, the U.S. Bureau of Reclamation determines allocations based on “forecasted reservoir inflows and Central Valley hydrologic conditions, amounts of storage in CVP reservoirs, regulatory requirements, and management of [wildlife] refuge water supplies” (USBR, 2017). For the State Water Project, California’s Department of Water Resources determines allocations based on “storage levels in Lake Oroville and San Luis Reservoir and the amount of runoff projected for the remaining year,” which includes precipitation and snowpack in the Sierra Nevada, while also taking into account “the various seasonal restrictions on pumping that the SWP must follow to protect threatened and endangered species as well as the flow needed to repel salinity in waterways of the Sacramento–San Joaquin Delta” (DWR, 2025). Differences in percentages across projects and contract types in the same year originate from permanent differences in legal priority as well as regional variation in water availability.

strumental variables model with two-way fixed effects using two-stage least squares. Since we observe the full population of domestic wells from the Well Completion Reports and can control for well-specific unobservables, we estimate a well-level panel model:

$$\begin{aligned} Y_{idt} &= \beta_1 \hat{SWD}_{dt} + \beta_2 HDD_{dt} + \beta_3 GDD_{dt} + \beta_4 P_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\ SWD_{dt} &= \gamma_1 SDA_{dt} + \gamma_2 HDD_{dt} + \gamma_3 GDD_{dt} + \gamma_4 P_{dt} + \lambda_t + \alpha_i + \mu_{idt}. \end{aligned} \quad (10)$$

The outcome, Y_{idt} , is now a binary variable indicating whether domestic well i reported failing in year t .²⁶ All other variables are defined as in equation (9), with the exception of α_i which denotes domestic well fixed effects. The first coefficient of interest, β_1 , represents the change in likelihood that a domestic well fails in a given year resulting from changes in agricultural surface water availability. Second, β_2 reflects the change in well failure probability from additional heat, driven by higher agricultural and domestic demands that result in groundwater depletion. 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 ground-water extraction on the intensive and extensive margins. For the extensive-margin response, we estimate the effect on the count of new agricultural wells constructed. To measure the rate of new well construction across space, it is necessary to introduce a common spatial unit of analysis. We aggregate new well counts to the DAUCO-level, which is the natural choice to match the unit of observation for surface water supplies. For this outcome, we use Poisson regression, for which the feasible instrumental variables estimator is a control function approach estimated with

²⁶While nonlinear estimation methods may be appropriate for some binary outcome models, maximum likelihood estimation requires units to have some variation in the outcome (Santos Silva and Tenreyro, 2010; Correia, Guimarães, and Zylkin, 2020). In our panel data context, this requirement excludes 95% of domestic wells that never experience a well failure. Therefore, we estimate this model with OLS to be fully representative of the population and its variation (or lack thereof).

Pseudo-Poisson Maximum Likelihood (PPML) (Wooldridge, 2015),

$$\begin{aligned} E[Y_{dt} | SWD, HDD, GDD, P, \alpha, \lambda] &= \\ \exp\{\beta_1 SWD_{dt} + \beta_2 HDD_{dt} + \beta_3 GDD_{dt} + \beta_4 P_{dt} + \alpha_d + \lambda_t + \phi \hat{\mu}_{dt}\} \end{aligned} \quad (11)$$

$$SWD_{dt} = \gamma_1 SDA_{dt} + \gamma_2 HDD_{dt} + \gamma_3 GDD_{dt} + \gamma_4 P_{dt} + \alpha_d + \lambda_t + \mu_{dt}.$$

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.²⁷ 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 C9 for a histogram). For robustness, we also report results using linear two-stage least squares (2SLS) alongside those estimated nonlinearly with Poisson in all tables where well construction is an outcome.

One potential threat to identification in the contemporaneous model 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, equation (11) would overstate 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

²⁷This 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).

and net new wells (new wells minus destroyed wells).

We also introduce dynamics into the well drilling decision to probe the possibility that our contemporaneous results are driven by intertemporal substitution. To do this, we estimate a linear instrumental variables model that incorporates lagged weather, mirroring equation (8), except the outcome is the count of new wells constructed in a DAUCO-year. In this specification, current and lagged surface water deliveries are treated as endogenous and are just-identified using current and lagged surface water allocations as instrumental variables.

These lagged estimates capture the net effect of past shocks on contemporaneous decisions, or the net effect of contemporaneous shocks on future decisions. They measure two phenomena. First, if farmers update beliefs about weather and surface water availability in response to past and contemporaneous shocks, then past and current negative shocks may induce farmers to construct more wells. This would result in a cumulative effect that is significantly larger than the contemporaneous effect. Alternatively, if weather shocks simply alter when a well is constructed, which we refer to as intertemporal substitution, then the coefficient estimates on lagged variables would take the opposite sign of the contemporaneous effect because drilling a well today offsets the need to drill one in the future.

6 Results

Damages: Groundwater Depletion

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 (9). 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 1-AF/acre reduction in surface water deliveries leads to a 2.9 ft decline in the groundwater levels, holding local 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 local extreme heat will lead to groundwater depletion through increased irrigation de-

mand and reduced recharge. 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).²⁸ Our estimates suggest that the surface water curtailments of 2021 resulted in a 2 ft decline in groundwater levels, and the extreme heat experienced locally in 2021 resulted in a 0.7 ft decline in groundwater levels.

Having identified the contemporaneous effect, we next seek to estimate the cumulative effect of surface water shocks on groundwater stocks, as captured by $\frac{dDTW_t}{ds_t}$ in equation (A4). To estimate the cumulative effect, we first need to choose a time horizon T for the distributed lag model presented in equation (8). In principle, new wells built in response to surface water scarcity can affect groundwater depletion for many years after they are built. We choose T by estimating a series of regressions that add lag terms in a stepwise fashion until the cumulative effect plateaus (i.e., until neither of the last lags on surface water or harmful degree days is statistically significant). Following this process, we choose a lag structure of three years ($T = 4$) (as shown in Table D1) to estimate the cumulative effect of surface water shocks on groundwater levels. If surface water scarcity affects groundwater depletion for more than four years, we will underestimate the cumulative effect.

Figure 6 plots the cumulative effect (i.e., the sum of contemporaneous and lagged coefficients) of a 1-AF/acre surface water shock on the depth to the water table in each of the four years following the surface water curtailment.²⁹ The pattern in Figure 6 indicates that surface water scarcity causes the greatest decline in groundwater stocks in the year in which it occurs ($T = 1$), and continues contributing to groundwater depletion for several more years. We attribute the latter to the persistent effect of surface water shocks on contemporaneous well construction and the lasting effect of durable well construction on groundwater extraction. Similar to Table 2, the con-

²⁸For 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 across DAUCOs. A one “within” standard deviation change is equal to 0.54 AF/acre for surface water and 14 HDD for extreme heat.

²⁹Table D1 reports annual effects of surface water shocks and harmful degree days over a four-year lag. Figure D1 plots the cumulative effect of a 1 HDD on the depth to the water table in each of the four years following surface water curtailments.

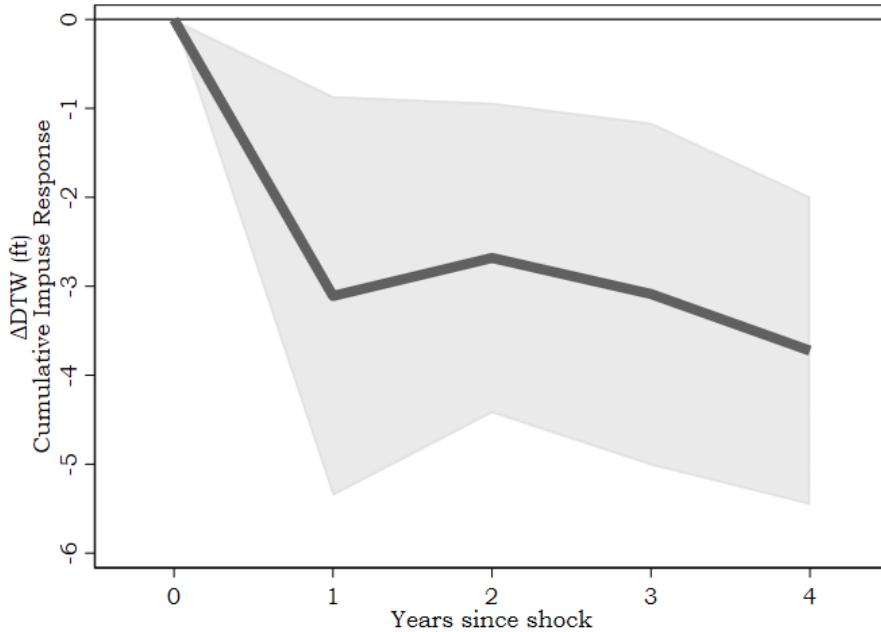
Table 2: Changes in Depth to the Groundwater

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-1.967 (0.674)	-1.533 (0.636)		
Ag SW Deliveries (AF/acre)			-3.684 (1.196)	-2.914 (1.174)
Harmful Degree Days		0.0308 (0.0160)		0.0309 (0.0115)
Observations	561,085	560,931	561,085	560,931
N Groups	83,782	83,762	83,782	83,762
KP F Stat			92.69	95.30
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 agricultural 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 well fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

temporaneous (year-1) effect of a 1-AF/acre reduction in surface water availability is a 3.1-foot increase in groundwater depth. After that, effects of surface water shocks persist over time. The cumulative change in groundwater levels continues to grow over time, increasing by almost 19% or to 3.7 feet three years after the initial shock. Between the second and fourth years following a surface water shock, groundwater levels decline by an additional 0.6 feet. However, the lags are not consistently jointly significant at the 5% on their own (Table D1), supporting the finding that the largest and most precise decline happens during the contemporaneous period as the shock.

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 from the IV model using allocations as an instrument for deliveries. Light shading reflects confidence intervals clustered at the DAUCO level.

Damages: Well Failures

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 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 percent-

Table 3: Linear Probability of Reported Well Failure

	Reduced Form		IV		
	(1)	(2)	(3)	(4)	(5)
Ag SW Allocation (AF/acre)	-0.016 (0.007)	-0.028 (0.016)			
Ag SW Deliveries (AF/acre)			-0.030 (0.010)	-0.056 (0.019)	-0.062 (0.016)
Harmful Degree Days		0.002 (0.001)		0.002 (0.001)	0.004 (0.002)
Observations	468,339	468,081	468,339	468,081	106,728
N Groups	78,068	78,025	78,068	78,025	17,790
KP F			10.699	10.283	44.165
Weights	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 well fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

age points, and a 1-AF/acre reduction in surface water increases well failures by 5.6 percentage points. Translated to our 2021 example, well failure probability increased by 3.9 percentage points (or 3,042 wells) as a result of surface water curtailments and by 4.4 percentage points (or 3,433 wells) due to extreme heat. If households must eventually replace these wells with deeper ones, assuming a conservative cost of \$10,000 per domestic well, that translates to potential damages of \$30.4 million and \$34.3 million from surface water and extreme heat shocks, respectively.³⁰ These

³⁰The state of California supports counties and local non-profit organizations to help households with both short-term solutions (e.g., temporary water storage tanks and hauled water) and long-term solutions (well replacement or connections to community water systems). In addition to the costs of drilling a new well, dry wells can lead to other interim health and sanitation challenges associated with the loss of reliable water supplies. In Table E1, we show that domestic well drilling responds to these shocks in the same direction as agricultural well drilling, but with smaller and less precise magnitudes relative to agricultural wells. Given that well failures are unexpected and drilling a replacement well is capital intensive, it is not surprising that households may not immediately respond to well failures in the same year and may take more temporary measures, like purchasing bottled water.

estimates are large when compared to the sample mean probability of well failure of 3% displayed in Table 1. Data limitations, specifically that the domestic well failure data span only a six year window, prevent us from estimating the distributed lag model on domestic well failures.

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.³¹ 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 domestic well failures are concentrated in lower-income communities and populations of color. To investigate these distributional effects, we decompose the treatment effects reported in column (4) of Table 3, calculating how much of the overall effects come from wells observed in each of several subgroups. We do this by estimating separate regressions that interact the outcome variable with subgroup indicators. This exercise mechanically apportions the main coefficient into subgroup contributions that reflect not only heterogeneous effects but also heterogeneous exposure to treatment.³² In Figure 7, 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. Even within this relatively disadvantaged population (i.e., domestic wells are already located in relatively low-income areas), the treatment effects are disproportionately attributable to relatively low-income and non-white census tracts. We also find the same patterns when defining subgroups using the state's "Disadvantaged Community" designation (see Appendix Figure C10).³³

Why are the weather-driven well failures concentrated in lower-income and more-Latino

³¹Information on dry well reporting, assistance and how it differs across regions can be found at: https://mydrywell.water.ca.gov/report/shortage_resources

³²For subgroups that are mutually exclusive and exhaustively defined, the coefficients sum to the full-sample coefficient. We define subgroups such that there are an equal number of domestic wells in each group. We do not observe the demographics of the well owners directly, so instead we assign characteristics based on the census tract in which the well is located.

³³Disadvantaged communities, defined by California Senate Bill 535, are census tracts that fall in the top-25 percentile of the CalEnviroScreen Index. This index is a composite measure of geographic, socioeconomic, public health, and environmental hazard criteria. As with income and race, the overall effects of heat and drought are driven by domestic well failures that occur within disadvantaged communities.

areas? There are three possibilities: larger treatment effects, greater exposure to weather shocks, and greater exposure to nearby cropland. To investigate, we tabulate each factor by subgroup in Appendix Table C2. We do not find much evidence of heterogeneous treatment effects: drought and heat appear to have similar effects on a given domestic well regardless of community demographics.³⁴ Instead, we find that non-white and low-income areas are more exposed to weather shocks and cropland: on average, they are located in areas with more crop acreage, and they experience greater variation in surface water allocations.

We conclude that the effects are concentrated in disadvantaged communities not primarily because their wells are shallower or lower quality but rather because they are simply more exposed to agriculture-driven groundwater depletion. Like many dimensions of environmental justice, this differential exposure is rooted in residential sorting, which reflects economic constraints, historical inequities in housing and labor markets, and the spatial concentration of agricultural employment. These results suggest that, absent changes to groundwater management, agricultural adaptation to climate change will bring more drinking water insecurity for the most disadvantaged communities.

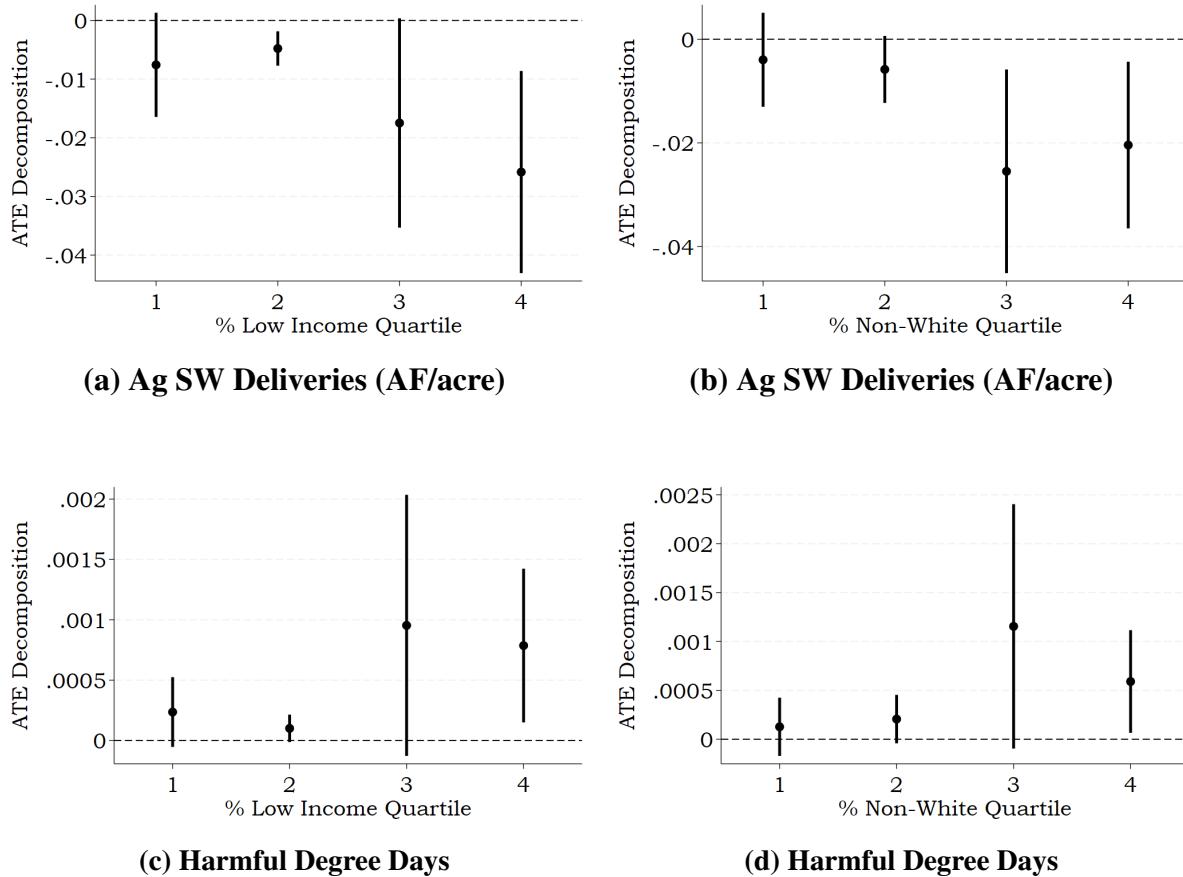
One Mechanism: Agricultural Well Construction

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 calculate the margins through which agricultural producers adapt and contribute to these damages. To do so, we first estimate the effects of contemporaneous 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 C3 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

³⁴These estimates come from standard heterogeneity analysis: regressions that interact the treatment variable with subgroup indicators. The results may be surprising given the data in Figure 2. The difference is that Figure 2 estimates the unconditional probability of failure, while here we estimate the change in the probability of failure that results from a fixed-size weather shock. Figure 2 also shows that wells in low-income and non-white areas are shallower, but the magnitude of the difference is not so large, and level differences are absorbed into the fixed effects anyway.

Figure 7: Decomposing Average Treatment Effects (ATE) by Local Demographics



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.

reduction in surface water and 1.3% more for every 1-HDD increase.³⁵ Assuming a uniform cost 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 C4 evaluates the effect of surface water and temperature shocks on the drilled depth of newly constructed wells. Agricultural wells are drilled 2.5 feet deeper in response to an additional harmful degree per day. Both agricultural and domestic well depths also appear to respond to water scarcity in the same year, though these estimates are imprecise.³⁶

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. We explore this possibility by estimating the effect of weather shocks on agricultural well destruction and net new wells (new wells minus destroyed wells). Results presented in Appendix Tables C5 and C6 provide little evidence that newly constructed wells are replacing existing ones. For surface water scarcity, the effects on well destruction are all much smaller than the effects on well construction, with large standard errors. For extreme heat, if anything, the estimates suggest that well owners destroy fewer wells in response to heat exposure.

To examine if our contemporaneous results are driven by intertemporal substitution, we augment our main specification to include three annual lags of surface water deliveries and harmful degree days. Figure 8 plots the cumulative effect of a 1-AF/acre surface water shock on new well construction in each of the four years following the surface water curtailment, and Table D2 reports individual annual effects in a stepwise fashion.³⁷ Incorporating lagged surface water deliveries increases the extensive-margin response from 12.4 new wells to 16.1 new wells from a 1-AF/acre reduction in surface water. This suggests that while intertemporal substitution may alter drilling decisions, on net, contemporaneous shocks and expectations about future weather, as measured by lagged surface water curtailments, drive the extensive-margin response. Similar to the dynamic

³⁵Recall that estimates must be transformed by $e^\beta - 1$ to be interpreted as a percent change for Poisson models.

³⁶Persistent groundwater depletion will require future groundwater wells to be drilled deeper, which will make well-drilling costs more expensive. The full extent of depletion is realized over time, however, which may be the reason why the estimates on the same-year surface water shocks are imprecise.

³⁷Figure D2 plots the cumulative effect of 1 HDD on new well construction in each of the four years following a harmful degree day. We do not estimate a distributed lag instrumental variables model using the Poisson transformation. This is because the control function approach outlined in equation (11) is incompatible with multiple nonlinear endogenous variables.

Table 4: Construction of New Agricultural Wells: IV and Control Function

	IV/2SLS		CF/PPML	
	(1)	(2)	(3)	(4)
Ag SW Deliveries (AF/acre)	-13.06 (4.584)	-12.38 (4.750)	-0.690 (0.262)	-0.620 (0.262)
Harmful Degree Days		0.111 (0.0329)		0.0128 (0.00261)
$\hat{\mu}$			0.732 (0.346)	0.767 (0.347)
Observations	9,660	9,240	8,568	8,400
N Groups	345	330	306	300
KP F Stat	94.90	96.97	-	-
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

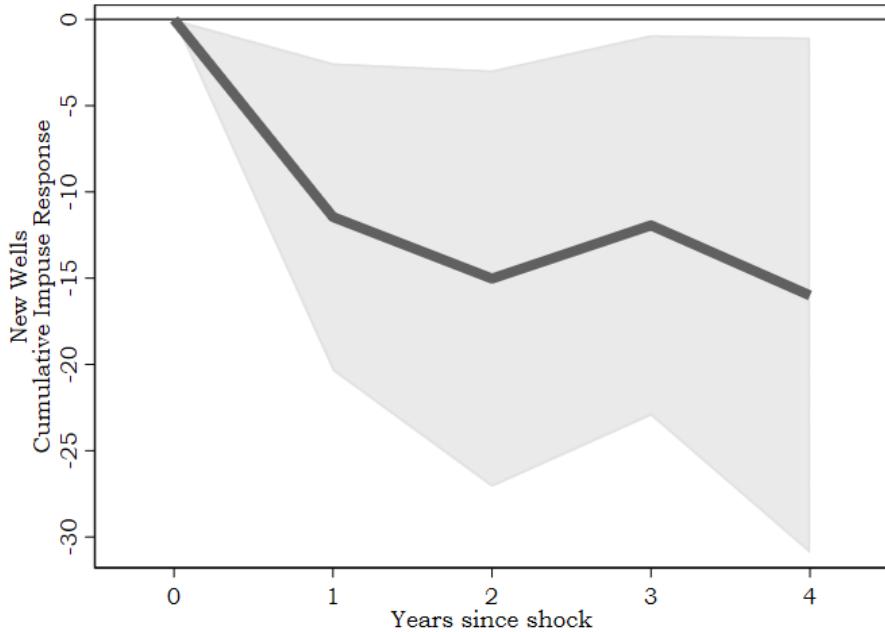
Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses. Columns (3) and (4) standard errors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

results on *DTW*, while the cumulative effect grows after four years and is statistically significant, the lags in these models are not jointly significant at the 5% level (Table D2). Our results imply that farmers respond to contemporaneous and past surface water scarcity by expanding groundwater irrigation and constructing wells that otherwise would not have 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 farmers' responses to shocks. To answer this question, we decompose the effect on groundwater depth into three margins: (1) the contemporaneous extensive margin of well construction, (2) the intensive

Figure 8: Cumulative Impulse Response of Surface Water Shocks on Well Construction



Note: Figure displays the cumulative impulse response of a single surface water shock (AF/acre) in the initial year. Dependent variable is the number of new wells constructed 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.

margin of increased pumping per well, which is unobserved, and (3) changes in recharge rates. From Section 3, we expect the extensive margin to be smaller than the intensive margin, but all three margins should be present and substantial.

We conduct two versions of the decomposition. First, we perform a static decomposition using the simple contemporaneous physical model from equation (3). Then, we apply the dynamic model from equation (A4) derived in Appendix A, which augments the decomposition to include the future well drilling margins. Table B1 lists the parameter values we use for these exercises. 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 draw from the literature specific to California: average annual groundwater extraction per well (q_{tau}), aquifer storativity (κ^{-1}), and the recharge rate

$(\sum_{\tau=t}^T \frac{\partial R_\tau(s_\tau)}{\partial s_t})$.³⁸ 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 with the static decomposition, 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. 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. However, a limitation of the static decomposition is that new wells constructed in a given year can only affect groundwater extraction in that year.

Including the dynamic effects of well construction, we estimate that the extensive margin (both contemporaneous and future) accounts for 41% of the effect of surface water scarcity on groundwater extraction. The cumulative effect of a one-year reduction in surface water of 1-AF/acre is a 0.45 AF/acre decline in groundwater stocks. Of this depletion, 40% is attributable to lost recharge, leaving a 0.26 AF/acre increase in groundwater extraction to be explained. The previously calculated contemporaneous intensive margin—increased pumping from existing wells—represents 35% of the decline in the water table, and 59% of the increase in extraction. The remainder, about 0.11 AF/acre of extraction, is attributable to the contemporaneous and future well-drilling margins.³⁹ This represents 41% of the increase in groundwater extraction or 25% of the total effect on groundwater depletion. Full details and algebra of the decomposition can be found in the Appendix section B and a summary of the margins in Table B2.

These results show that, as expected, new well construction plays a meaningful role in how

³⁸This recharge rate captures the total recharge that results from a shock at one point in time. It is possible that some of this recharge occurs in later periods since water takes time to percolate through the ground into the aquifer.

³⁹The well-drilling margin is inclusive of both cumulative pumping from wells drilled in the contemporaneous year and future wells drilled as a result of the shock in the initial year. For the latter, from Figure 8 and Table D2, we know that new well construction increases about 31% more beyond the initial year from the sum of the lagged response ($\frac{-16.07}{-12.38}$).

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 meaningful share is indeed due to behavioral margins of adjustment, through a mechanism that we 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 drought and heat shocks have 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 exacerbates externalities to domestic well owners. Importantly, these external costs are heavily borne 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 recently been proposed or enacted as solutions to manage groundwater with some success (Ayres, Meng, and Plantinga, 2021; Burlig, Preonas, and Woerman, 2024; 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 (Kuwayama and Brozović, 2013). 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; Auffham-

mer, 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, 2024).

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 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 dimension of these effects over time.

First, the stock of wells drilled is a function of current and past surface water shocks and weather realizations, $w_\tau(\mathbf{s}_\tau)$, where \mathbf{s}_τ is a vector of current and past weather shocks at time τ .⁴⁰ The stock of wells at time τ can be characterized as the initial stock of wells and the sum of wells drilled between period $\mu = 1$ and year τ . The annual change in wells is a function of weather shocks experienced between 1 and μ :

$$\begin{aligned} w_\tau(\mathbf{s}_\tau) &= w_{\tau-1} + \Delta w_\tau(s_\tau) \\ &= w_{\tau-2} + \Delta w_{\tau-1}(\mathbf{s}_{\tau-1}) + \Delta w_\tau(\mathbf{s}_\tau) \\ &= w_0 + \sum_{\mu=1}^{\tau} \Delta w_\mu(\mathbf{s}_\mu) \end{aligned} \tag{A1}$$

Second, well drilling in period t affects the depth to the water table in the future:

$$\begin{aligned} DTW_T(s_t, \dots, s_T) &= DTW_t + \kappa \sum_{\tau=t}^T C_\tau(s_\tau) - \kappa \sum_{\tau=t}^T R_\tau(s_\tau) \\ &= DTW_t + \kappa \sum_{\tau=t}^T q_\tau(s_\tau) w_\tau(s_\tau) - \kappa \sum_{\tau=t}^T R_\tau(s_\tau) \\ &= DTW_t + \kappa \sum_{\tau=t}^T q_\tau(s_\tau) \left(w_0 + \sum_{\mu=t}^{\tau} \Delta w_\mu(\mathbf{s}_\mu) \right) - \kappa \sum_{\tau=t}^T R_\tau(s_\tau) \end{aligned} \tag{A2}$$

Measured at some future period T , the depth to the water table is the sum of the starting water table depth, cumulative groundwater consumption between period t and T , and the sum of current and future recharge between period t and T . Note here that pumping intensity, $q_t(s_t)$ is

⁴⁰For expositional ease, we restrict our model to surface water shocks, but it easily extends to heat shocks.

only dependent on the current period shock.

Expanding the sums for convenience, to keep current-year shocks separate from future years' shocks:

$$\begin{aligned}
DTW_T(s_t, \dots, s_T) &= DTW_t + \kappa \sum_{\tau=t}^T q_\tau(s_\tau) \left(w_0 + \sum_{u=t}^\tau \Delta w_u(\mathbf{s}_u) \right) - \kappa \sum_{\tau=t}^T R_\tau(s_\tau) \\
&= DTW_t + \kappa \underbrace{q_t(s_t) w_t(\mathbf{s}_t)}_{\text{Contemporaneous consumption}} + \kappa \sum_{\tau=t+1}^T q_\tau(s_\tau) \left(\underbrace{w_t(\mathbf{s}_t)}_{\text{Future pumping from stock of wells at } t} + \underbrace{\sum_{u=t+1}^\tau \Delta w_u(\mathbf{s}_u)}_{\text{Wells drilled in years after } t} \right) - \kappa \sum_{\tau=t}^T R_\tau(s_\tau)
\end{aligned} \tag{A3}$$

Here, depth to the groundwater in future period T is a function of five unique terms: (1) Starting depth in year t , DTW_t , (2) consumption in the first year t , (3) the sum of future pumping from the stock of wells at time t that persistently pump each year in the future, (4) pumping from the sum of new wells that are drilled after year t , and (5) sum of each year's recharge. Each of these terms can be a function of surface water supplies, and therefore, may be important margins for appropriate water accounting.

With these general dynamic forms of well drilling and depth to the water table, we can now evaluate the cumulative effect of a surface water shock in year t on groundwater availability in future period T as:

$$\begin{aligned}
\underbrace{\frac{dDTW_T}{ds_t}}_{\text{cumulative effect}} &= \kappa \left[\underbrace{w_t(\mathbf{s}_t) \times \frac{dq_t(s_t)}{ds_t}}_{\text{contemporaneous intensive margin}} + \underbrace{q_t(s_t) \times \frac{\partial w_t(\mathbf{s}_t)}{\partial s_t}}_{\text{contemporaneous extensive margin}} + \right. \\
&\quad \underbrace{\sum_{\tau=t+1}^T q_\tau(s_\tau) \times \frac{\partial w_t(\mathbf{s}_t)}{\partial s_t}}_{\text{future pumping from wells drilled in } t} + \underbrace{\sum_{\tau=t+1}^T \sum_{f=0}^{T-\tau} q_{\tau+f}(s_{\tau+f}) \times \frac{\partial w_\tau(\mathbf{s}_\tau)}{\partial s_t}}_{\text{pumping from future drilled wells from } s_t} - \left. \underbrace{\sum_{\tau=t}^T \frac{\partial R_\tau(s_\tau)}{\partial s_t}}_{\text{recharge margin}} \right].
\end{aligned} \tag{A4}$$

The marginal effect of a weather shock on groundwater depth can now be decomposed into five mechanisms. First, farmers may respond to a current shock by pumping more from each preexisting well (the contemporaneous intensive margin): $w_t(\mathbf{s}_t) \frac{dq_t}{ds_t}(s_t)$. Second, farmers may

construct new wells and pump from those new wells today (the contemporaneous extensive margin): $q_t \frac{\partial w_t}{\partial s_t}(\mathbf{s}_t)$. Third, wells constructed today will continue to pump groundwater in future years: $\frac{\partial w_t}{\partial s_t} \sum_{\tau=t+1}^T q_\tau(s_\tau)$. Fourth, a contemporaneous weather shock will impact future drilling decisions and persistent pumping from those wells drilled in the future until T, $\sum_{\tau=t+1}^T \sum_{f=0}^{T-t} q_{\tau+f}(s_{\tau+f}) \times \frac{\partial w_{\tau+f}(s_{\tau+f})}{\partial s_t}$. Fifth, weather shocks will have contemporaneous and future effects on recharge: $\sum_{\tau=t}^T \frac{\partial R_\tau}{\partial s_t}(\mathbf{s}_\tau)$.

B Calculations for Decomposition Exercise

Once we obtain empirical estimates and assign numerical values to the parameters in equation (A4), we can input the values and clarify the magnitude of each margin’s contribution to the gross effect. Of the five mechanisms, we already know three from the static decomposition; only the “future well drilling from s_t ” and “future pumping from wells drilled in t ” remain. The former is challenging to estimate directly and in full.⁴¹ Instead, we back out the gross value of the future well drilling margins from other terms we have already estimated. The intuition is that the future extensive margins are the only mechanisms that affect periods beyond the contemporaneous one, so all lagged effects of weather shocks on groundwater depth can be attributed to them:

$$\frac{dDTW_T}{ds_t} - \frac{dDTW_t}{ds_t} = \kappa \left[\underbrace{\sum_{\tau=t+1}^T q_\tau(s_\tau) \times \frac{\partial w_t(\mathbf{s}_t)}{\partial s_t}}_{\text{future pumping from wells drilled in } t} + \underbrace{\sum_{\tau=t+1}^T q_\tau(s_\tau) \times \frac{\partial w_\tau(\mathbf{s}_\tau)}{\partial s_t}}_{\text{future drilled wells from } s_t} \right] = \sum_{\tau=t+1}^T \frac{dDTW_\tau}{ds_t}. \quad (\text{B1})$$

Table B2 provides a summary of this accounting exercise. In Table D1, we show that the cumulative effect of a single shock in the initial year grows to a 3.72-foot reduction per AF/acre of surface water supplies by the fourth year after the shock. In volume, this translates to a 0.45 AF/acre reduction after multiplying by the aquifer storativity coefficient, κ . We assign the maximum plausible decrease in recharge based on water balance data from the California Department of Water Resources. Then, the remainder must be derived from human behavioral margins of adjustment. From the contemporaneous exercise and estimates on contemporaneous well drilling, we calculate that approximately 0.01 AF/acre or 3% of the gross effect comes from new wells drilled in the first year of the shock. We can then back out the size of the unobserved contemporaneous intensive margin response, which we calculate to be 0.16 AF/acre or 35% of the gross effect. Future well drilling and groundwater pumped from new wells in response to surface water shocks then

⁴¹This 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 assign 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 .

account for the remaining 22% of the cumulative gross effect on groundwater levels. The total well drilling response accounts for 25% of the total effect or 41% of the behavioral response.

Table B1: Parameter Values for Decomposition

Parameter	Value	Units	Description
$\frac{dDTW_t}{ds_t}$	-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.
$\frac{dDTW_T}{ds_t}$	-3.72	ft per AF/ac	Cumulative future change in DTW per AF/acre change in surface water. Results from figure 6 and table D1
κ	8.33	unitless	Inverse storativity or specific yield Department of Water Resources (2020)
$\sum_{\tau=t}^T \frac{\partial R_\tau(s_\tau)}{\partial s_t}$	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.
$\frac{\partial w_t}{\partial s_t}$	-4.60×10^{-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 4 Column 4 multiplied by the total annual average of new agricultural wells divided by California crop acreage.
q_τ	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_τ	8.60×10^{-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.

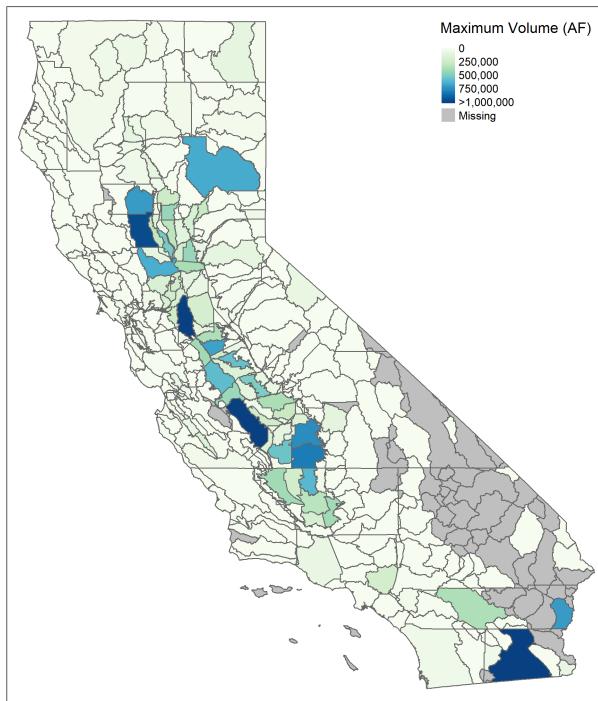
Note: Table reports estimated and calculated values for parameters in the decomposition of intensive and extensive margin effects presented in equations (3) and (A4). California Water Balance Data used to calculate recharge coefficient can be accessed at <https://data.cnra.ca.gov/dataset/water-plan-water-balance-data>

Table B2: Calculating the Margins of Response

Margin	Value	% of Gross Effect	Description
Gross Effect:			
$\frac{dDTW_T}{ds_t} \times \frac{1}{\kappa}$	0.45 AF/acre	-	Cumulative gross effect on groundwater levels. Estimated in Table D1.
$\frac{dDTW_t}{ds_t} \times \frac{1}{\kappa}$	0.35 AF/acre	-	Contemporaneous gross effect on groundwater levels. Estimated in Table 2.
Physical Margin:			
$\sum_{\tau=t}^T \frac{\partial R_\tau(s_\tau)}{\partial s_t}$	0.18 AF/acre	40%	Maximum potential lost recharge from ds_t . Assigned from DWR Water Balance Data.
Behavioral Margins:			
$w_t(\mathbf{s}_t) \times \frac{dq_t(s_t)}{ds_t}$	0.16 AF/acre	35%	Contemporaneous intensive margin from ds_t . Calculated from equation (3).
$q_t(s_t) \times \frac{\partial w_t(s_t)}{\partial s_t}$	0.01 AF/acre	3%	Contemporaneous pumping from new wells drilled from ds_t . Estimated in Table 4.
$\sum_{\tau=t+1}^T q_\tau(s_\tau) \times \frac{\partial w_\tau(s_\tau)}{\partial s_t}$	0.10 AF/acre	22%	Future pumping from new wells drilled from ds_t . Calculated from equation (A4).

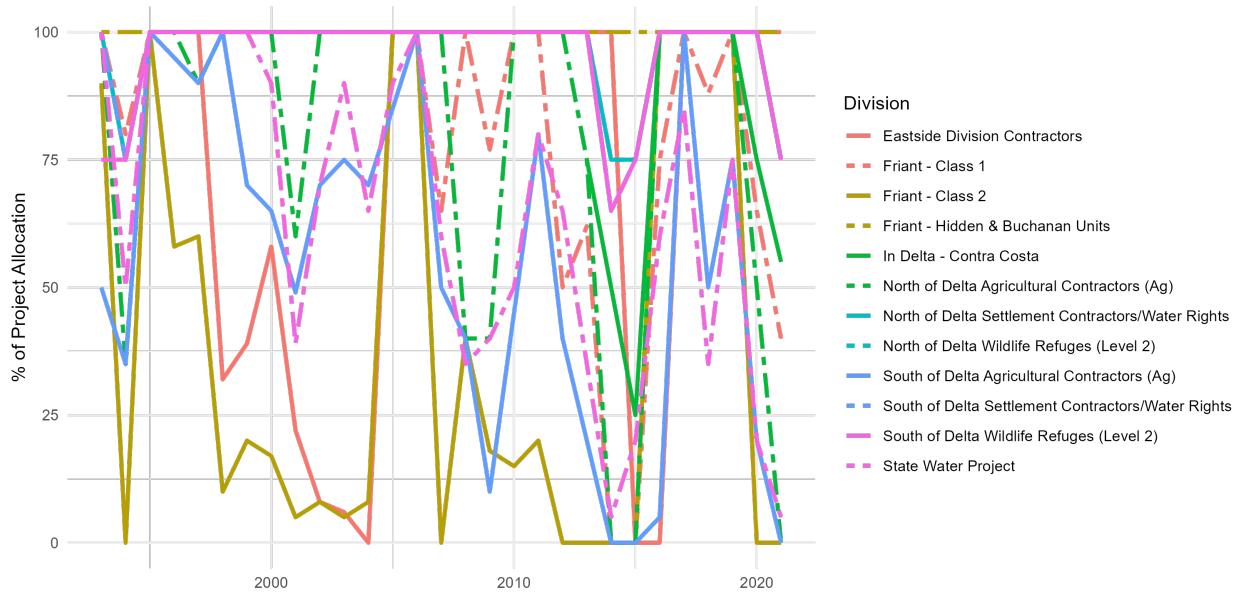
C Supplementary Figures and Tables

Figure C1: Maximum Contracted Surface Water Volumes (AF) by DAUCO



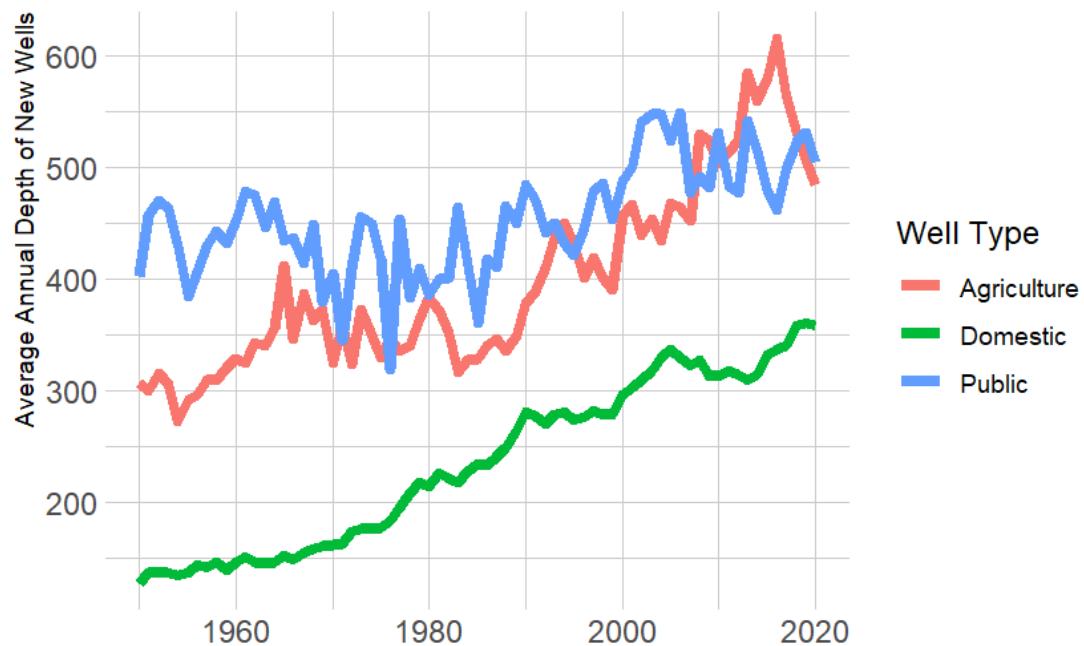
Note: Figure displays the time-invariant maximum volume of surface water that each district can potentially receive. Water contracts may be with the State Water Project, the Central Valley Project, the Lower Colorado River Project, or individual water rights. The variety of sources and water projects throughout California contributes to cross-sectional variation in the potential magnitude of water deliveries.

Figure C2: Temporal Variation in Allocation Percentages by Water Project Divisions



Note: Figure displays the time-varying allocation percentages for each of the water projects in California. Allocation percentage for each project is determined by the availability of water available in each project's reservoirs or snowpack levels near reservoirs. Because of this, allocation percentages within the same year may still differ across the state depending on environmental conditions at the source.

Figure C3: Depth of Drilled Wells Over Time



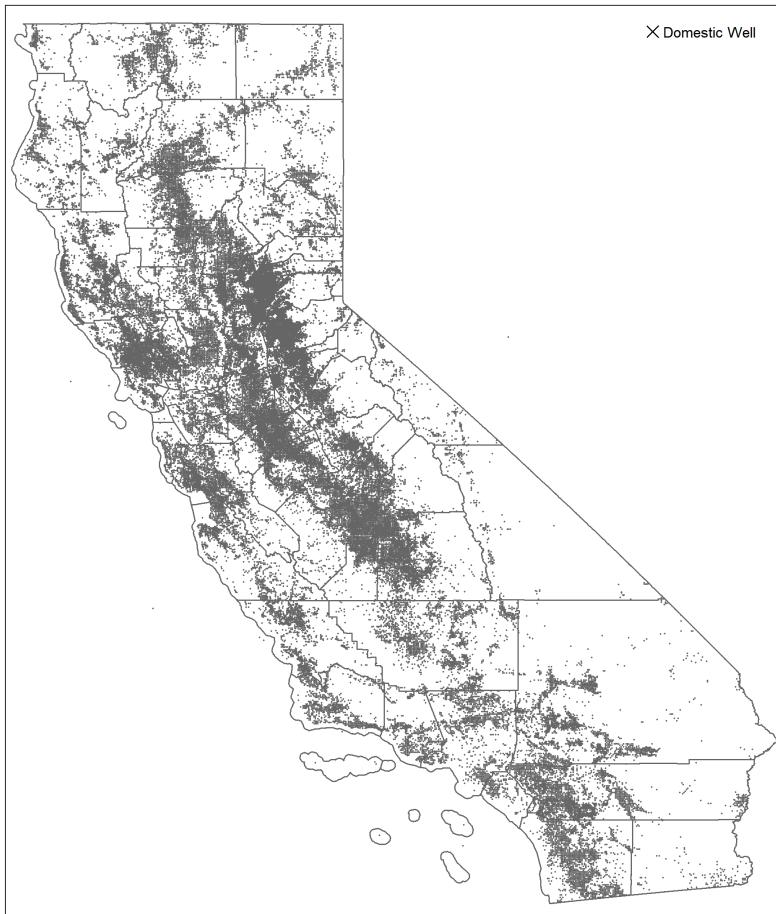
Note: Figure displays the annual average depth of new wells over time by well type. The average agricultural and domestic well is drilled over 200 feet deeper than in 1950.

Figure C4: Distribution of time between construction and permit date



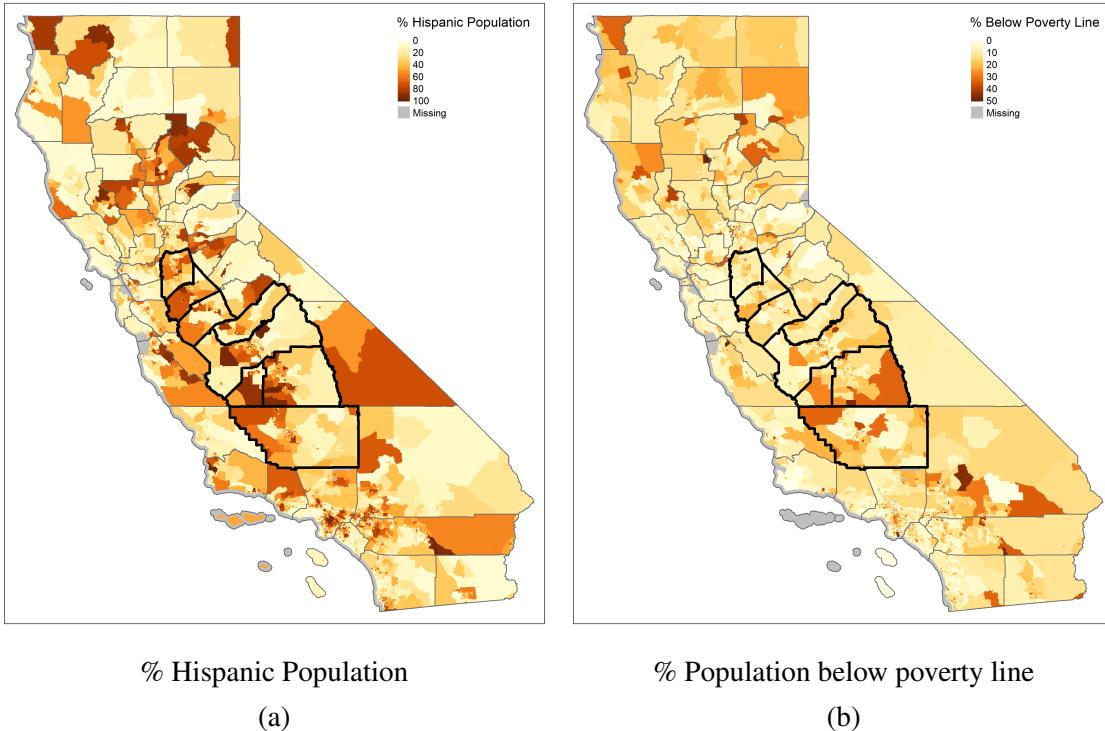
Note: Figure displays the density of time between a new well's permit date and its completed construction date. Permit dates in well completion reports are only available after 2015, and therefore, this represents only about 10% of the full agricultural well sample.

Figure C5: Location of Domestic Wells



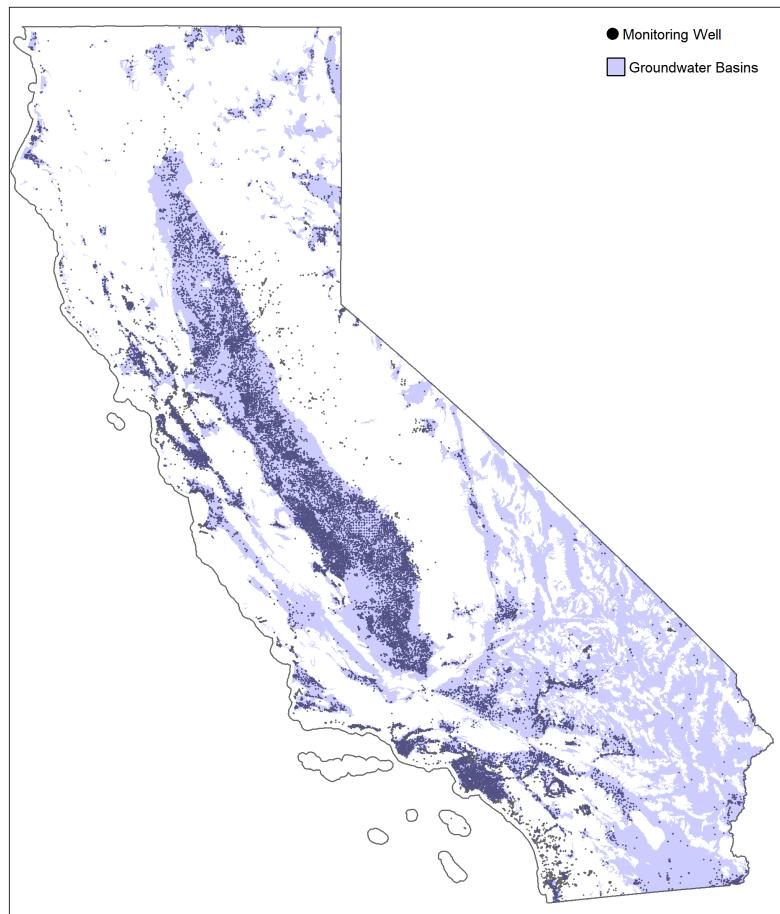
Note: Figure shows the location of domestic groundwater wells constructed. Data are from Well Completion Reports from DWR.

Figure C6: Population Demographics in California



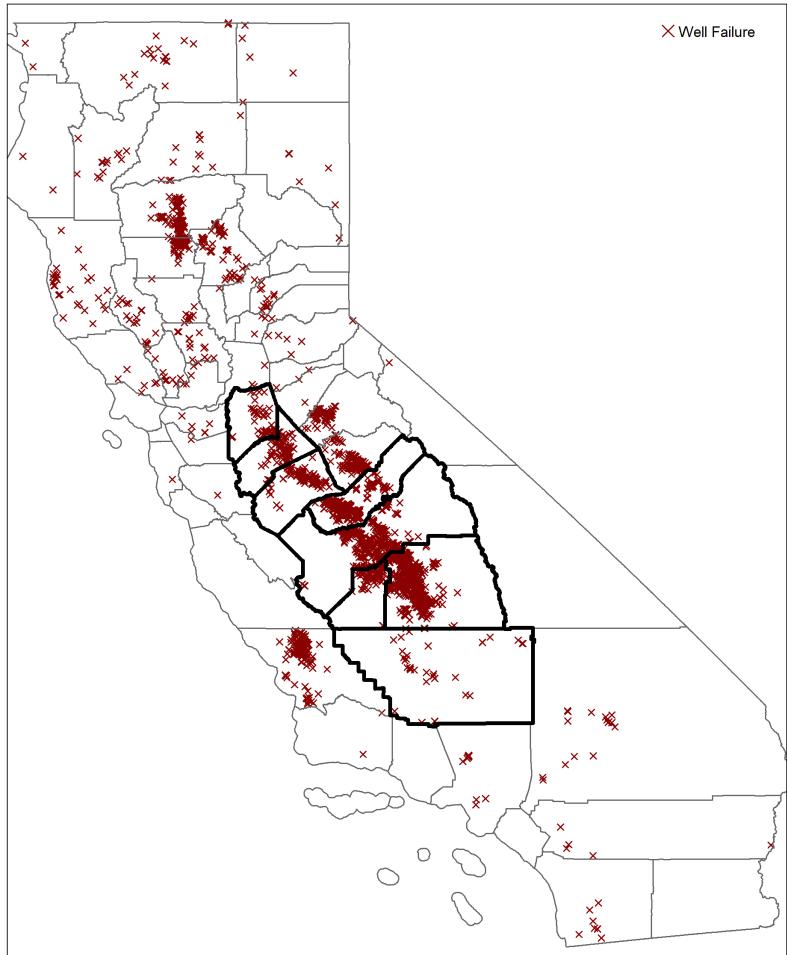
Note: Figure displays demographics at the Census tract level using data from 2020 (Manson et al., 2022). Panel (a) plots the percentage of the population that identifies as Hispanic. Panel (b) plots the percentage of households that fall below the federal poverty line for their household size. Bold county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

Figure C7: Location of Monitoring Wells in California Groundwater Basins



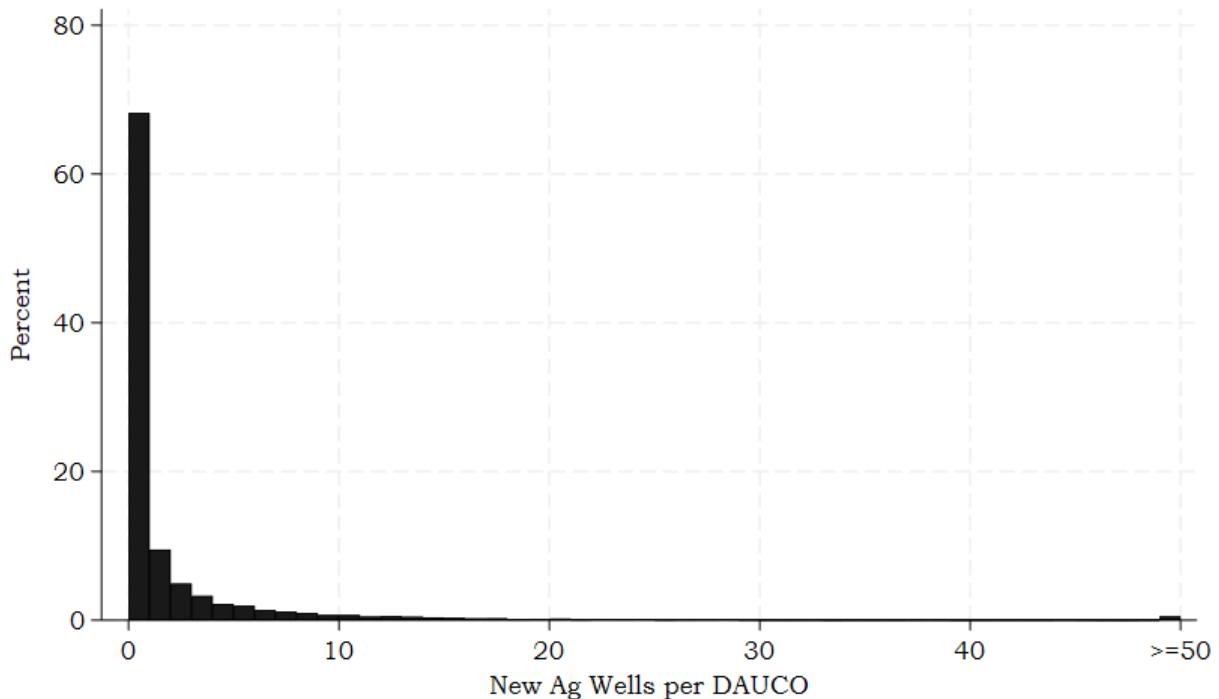
Note: Figure displays the locations of groundwater monitoring wells and California's principle groundwater basins. Each dot displays a unique groundwater monitoring well reported in our dataset. The blue shaded areas display the locations of Bulletin 118 groundwater basins in California.

Figure C8: Locations of Reported Well Failures, 2014-2020



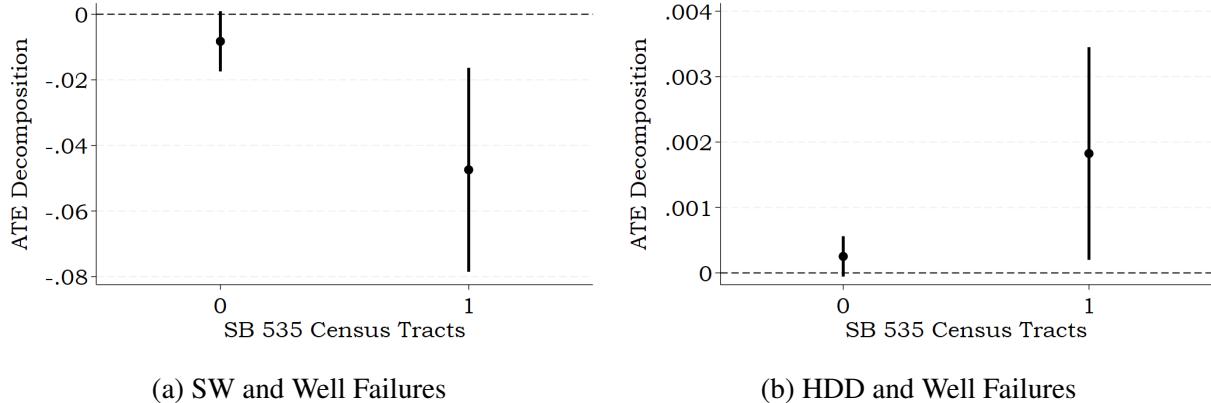
Note: Figure plots the locations of all reported well failures from 2014-2020 from the Dry Wells Reporting System from California DWR. Counties in the San Joaquin Valley have a thick border, and a large share of reported well failures occur in these counties.

Figure C9: 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.

Figure C10: Treatment Effects on Well Failures Decomposed by SB535 Census Tract Designation



Note: Figure shows the share of the treatment effect on surface water and heat by SB535 census tract designation (i.e. treatment effects for two groups sum to the pooled treatment effect in Table 3). The dependent variable is a binary outcome if a domestic groundwater reported a failure that year multiplied by an indicator denoting SB535 census tracts. All regressions are weighted by the DAUCO crop acres, include year and DAUCO fixed effects, and control for local weather.

Table C1: Agricultural SW Deliveries: First-Stage Results

	(1)	(2)	(3)	(4)
	Ag SW Deliveries			Ag SW Allocations
Ag SW Allocations (AF/acre)	0.588 (0.0460)	0.531 (0.0540)		
Harmful Degree Days		-0.000353 (0.00172)	-0.00140 (0.00238)	-0.00197 (0.00131)
Growing Degree Days		0.000184 (0.0000431)	0.0000708 (0.0000665)	-0.000213 (0.000138)
Annual Precipitation		-0.000461 (0.000202)	-0.000759 (0.000151)	-0.000560 (0.000204)
Observations	9,996	9,996	9,996	9,996
N Cluster	357	357	357	357
F Stat	94.83	54.22	16.57	3.62
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: In columns 1-3, the dependent variable is Ag SW deliveries per crop acre in levels from 1993-2021. In column 4, the dependent variable is Ag SW allocation per crop acre in levels. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors in parentheses and F-statistics are adjusted for clustering at the DAUCO level.

Table C2: Decomposition of Effects on Well Failures by Demographics

(a) Decomposition of Drought-Induced Well Failures by Demographics

Domestic Wells		$\hat{\beta}^{SW}$	DAUCO Crop Acres	IQR SW	$\hat{\beta}^{SW}$	%	of
<i>Panel A: Statewide</i>							
–	80234	-.056	40299	-.2	-.056	100	
<i>Panel B: By Non White % Quartile</i>							
1	20094	-.096	15438	-.08	-.004	7	
2	20075	-.047	27001	-.16	-.006	10	
3	20147	-.055	54537	-.26	-.025	46	
4	19918	-.061	64269	-.3	-.020	37	
<i>Panel C: By Low Income % Quartile</i>							
1	20181	-.057	31582	-.19	-.008	14	
2	20393	-.063	29378	-.15	-.005	9	
3	19998	-.045	39801	-.23	-.017	31	
4	19662	-.062	61166	-.23	-.026	46	

(b) Decomposition of Heat-Induced Well Failures by Demographics

Domestic Wells		$\hat{\beta}^{HDD}$	DAUCO Crop Acres	IQR HDD	$\hat{\beta}^{HDD}$	%	of
<i>Panel A: Statewide</i>							
–	80234	.0021	40299	15.72	.0021	100	
<i>Panel B: By Non White % Quartile</i>							
1	20094	.0016	15438	14.39	.0001	6	
2	20075	.0017	27001	15.32	.0002	10	
3	20147	.0027	54537	16.23	.0012	56	
4	19918	.0018	64269	16.94	.0006	28	
<i>Panel C: By Low Income % Quartile</i>							
1	20181	.0018	31582	15.98	.0002	11	
2	20393	.0016	29378	14.59	.0001	5	
3	19998	.0029	39801	15.72	.0010	46	
4	19662	.0017	61166	16.62	.0008	38	

Note: Tables report (1) total count of domestic wells; (2) subgroup-specific treatment effect, estimated in a regression that interacts the treatment variable with subgroup indicators; (3) average DAUCO crop acres; (4) the average interquartile range (IQR) of the treatment variable – surface water allocations or heating degree days (HDD); (5) the subgroup's contribution to the overall treatment effect, estimated in separate regressions that interact the outcome variable with quartile indicators; and (6) the subgroup's contribution as a percentage of the overall treatment effect.

Table C3: Construction of New Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-7.180 (2.665)	-6.581 (2.596)	-0.333 (0.131)	-0.278 (0.124)
Harmful Degree Days		0.115 (0.0390)		0.00897 (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.

Table C4: 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 (18.16)	-23.14 (21.67)	-8.170 (7.699)	-37.03 (29.10)	-34.48 (32.23)	-14.14 (14.34)
Ag SW Deliveries (AF/ crop acre)						
Harmful Degree Days	1.431 (0.624)	2.592 (1.108)	0.346 (0.244)	1.340 (0.563)	2.449 (1.019)	0.319 (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					
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 (5) 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 C5: Destruction of Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation per crop acre (AF)	0.115 (0.193)	0.164 (0.228)	-0.0903 (0.140)	-0.00591 (0.143)
Harmful Degree Days		-0.00215 (0.00778)		-0.0228 (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 C6: Net New Agricultural Well Constructed per DAUCO

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-7.308 (2.718)	-6.755 (2.633)		
Ag SW Deliveries(AF/acre)			-13.29 (4.662)	-12.71 (4.794)
Harmful Degree Days		0.118 (0.0364)		0.113 (0.0299)
Observations	10416	9996	10416	9996
N Cluster	372	357	372	357
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 constructed wells minus destructed agricultural wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the reduced-form, OLS model. Columns (3) and (4) report coefficients the instrumental variables model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

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

D Dynamic Empirical Estimation Results

Table D1 reports the dynamic effects up for up to 3 lag shocks on surface water deliveries and harmful degree days. The cumulative effects of this table are plotted in Figures 6 and D1.

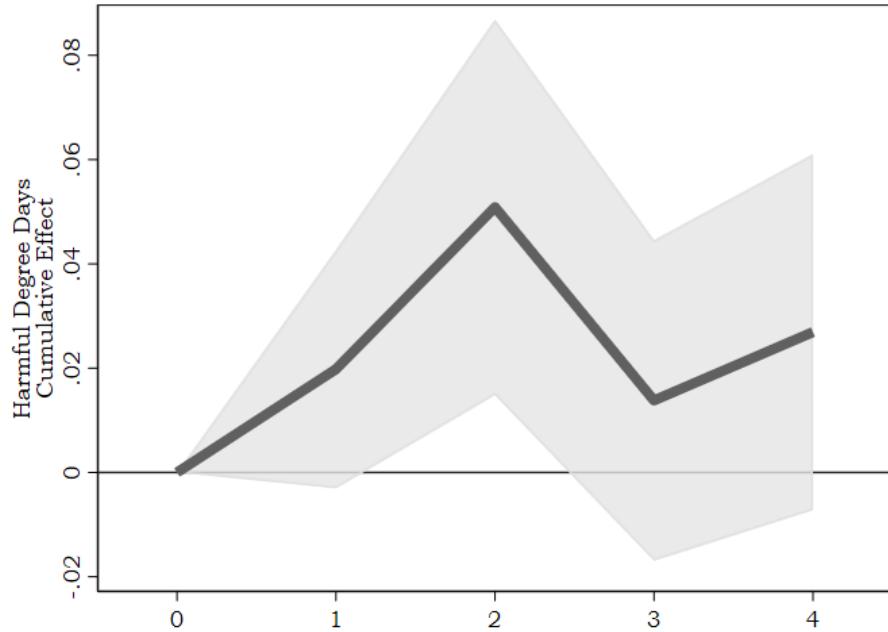
Table D2 considers the dynamics of agricultural well drilling. We report the results a linear IV for well construction, similar to columns (1) and (2) of Table 4 but now supplemented with up to three lagged years of agricultural surface water deliveries. Columns (2) through (4) each add an additional lag. In these specifications, deliveries are instrumented with surface water allocations.

Table D1: Lagged Changes in Groundwater Depth

	(1)	(2)	(3)	(4)
	ΔDTW			
Ag SW Deliveries (AF/ crop acre)	-2.914 (1.176)	-2.769 (1.146)	-2.828 (1.146)	-3.109 (1.146)
L.Ag SW Deliveries (AF/ crop acre)		0.433 (0.654)	0.200 (0.629)	0.428 (0.625)
L2.Ag SW Deliveries (AF/ crop acre)			-0.258 (0.699)	-0.406 (0.724)
L3.Ag SW Deliveries (AF/ crop acre)				-0.637 (0.418)
$\sum \beta_{deliveries}$	-2.914	-2.335	-2.887	-3.724
$p_{cumulative}$	0.0138	0.00812	0.00446	0.0000336
p_{lag}		0.508	0.896	0.0916
Harmful Degree Days	0.0309 (0.0115)	0.0226 (0.0126)	0.0245 (0.0130)	0.0198 (0.0117)
L.Harmful Degree Days		0.0168 (0.0100)	0.0307 (0.0118)	0.0311 (0.0126)
L2.Harmful Degree Days			-0.0207 (0.00978)	-0.0371 (0.0130)
L3.Harmful Degree Days				0.0131 (0.0109)
$\sum \beta_{hdd}$	0.0309	0.0394	0.0345	0.0269
$p_{cumulative}$	0.00795	0.00455	0.0340	0.123
p_{lag}		0.0943	0.0176	0.0236
Observations	560,931	555,846	550,874	545,710

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. All regressions are weighted by the DAUCO crop acres multiplied by the inverse density of monitoring wells and include year and well fixed effects and control for local weather. Standard errors are clustered at the DAUCO level and are reported in parentheses. $p_{cumulative}$ reports the p-value for a t-test of whether the sum of the contemporaneous and lagged coefficients is different than zero. p_{lags} reports the p-values for a joint significance test of only the lagged terms.

Figure D1: Cumulative Impulse Response of Harmful Degree Days on ΔDTW



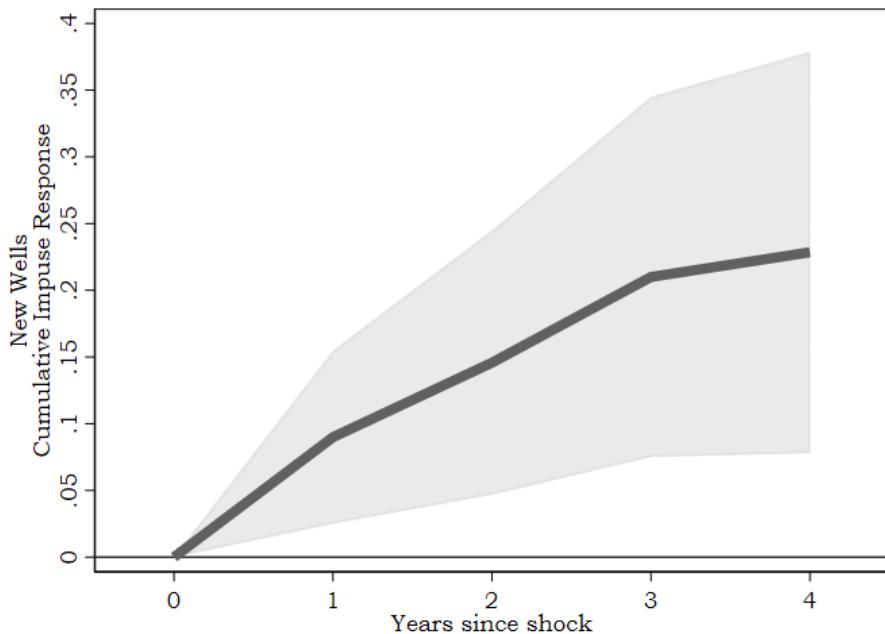
Note: Figure displays the cumulative impulse response of a single harmful degree day in the initial year. Dependent variable is ΔDTW and the dark line reflects the sum of contemporaneous and lagged coefficients on harmful degree days for each year since the initial shock. Light shading reflects confidence intervals clustered at the DAUCO level.

Table D2: Lagged Agricultural Well Construction

	(1)	(2)	(3)	(4)
	New Ag Wells per DAUCO			
Ag SW Deliveries (AF/ crop acre)	-12.38 (4.750)	-11.51 (4.450)	-11.53 (4.582)	-11.45 (4.537)
L.Ag SW Deliveries (AF/ crop acre)		-3.512 (2.858)	-2.999 (2.779)	-3.602 (3.207)
L2.Ag SW Deliveries (AF/ crop acre)			1.377 (2.355)	3.089 (2.505)
L3.Ag SW Deliveries (AF/ crop acre)				-4.109 (2.853)
$\sum \beta_{deliveries}$	-12.38	-15.02	-13.15	-16.07
$p_{cumulative}$	0.00913	0.00877	0.0277	0.0355
p_{lags}		0.218	0.318	0.287
Harmful Degree Days	0.111 (0.0329)	0.0981 (0.0349)	0.0971 (0.0318)	0.0897 (0.0327)
L.Harmful Degree Days		0.0809 (0.0397)	0.0848 (0.0426)	0.0548 (0.0390)
L2.Harmful Degree Days			0.0551 (0.0247)	0.0643 (0.0239)
L3.Harmful Degree Days				0.0174 (0.0237)
$\sum \beta_{hdd}$	0.111	0.179	0.237	0.226
$p_{cumulative}$	0.000760	0.00484	0.00171	0.00302
p_{lags}		0.0413	0.0498	0.0548
Observations	9,240	8,910	8,580	8,250
N Cluster	330	330	330	330

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 and control for local weather. Standard errors are clustered at the DAUCO level and are reported in parentheses. $p_{cumulative}$ reports the p-value for a t-test of whether the sum of the contemporaneous and lagged coefficients is different than zero. p_{lags} reports the p-values for a joint significance test of only the lagged terms.

Figure D2: Cumulative Impulse Response of Harmful Degree Days on Well Construction



Note: Figure displays the cumulative impulse response of a single harmful degree day in the initial year. Dependent variable is ΔDTW and the dark line reflects the sum of contemporaneous and lagged coefficients on harmful degree days for each year since the initial shock. Light shading reflects confidence intervals clustered at the DAUCO level.

E Additional Empirical Specifications

We conduct two falsification tests of our primary model. First, Table E1 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 E2. 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 C3 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

We also test whether our results on well failure are robust to an alternative specification choice. Instead of running a linear probability model at the well level, we aggregate the count of domestic well failures to the DAUCO level and use the failure counts as an outcome. DAUCOs have different numbers of domestic wells at a baseline, so we additionally weight the regression by the count of total domestic wells in the DAUCO. These results (Table E3) are consistent with results at the well level. A 1-AF/acre surface water causes 54 more domestic wells to fail in a DAUCO. Each additional HDD causes two additional wells to fail.

A final robustness check tests whether our results are sensitive to our definition of harmful degree days. Instead of measuring exposure above 32° , we include a measure of exposure above 29° C, which is commonly used to measure heat exposure in nonirrigated agriculture in the U.S. Midwest (Schlenker and Roberts, 2009; Burke and Emerick, 2016). Results from the full specification of each outcome are reported in Table E4. In general, the coefficients on degree days above 29° C across outcomes are very similar to those on 32° in the corresponding models.

Table E1: Construction of New Domestic Wells

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-1.534 (1.582)	-1.021 (1.535)	-0.0657 (0.0783)	-0.0128 (0.0641)
Harmful Degree Days		0.0774 (0.0477)		0.00950 (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 E2: Construction of New Agricultural Wells: Municipal and Industrial Surface Water

	OLS		PPML	
	(1)	(2)	(3)	(4)
M&I SW Allocation per Acre	19.71 (28.88)	23.36 (28.91)	1.407 (1.300)	1.459 (1.257)
Harmful Degree Days		0.115 (0.0422)		0.0143 (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.

Table E3: Weather Shocks and the Count of Domestic Well Failure: DAUCO-Level Regressions

	Reduced Form		IV/2SLS	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-15.055 (7.416)	-27.535 (15.980)		
Ag SW Deliveries (AF/acre)			-28.534 (11.140)	-54.814 (21.043)
Harmful Degree Days		2.145 (0.971)		2.104 (0.932)
Observations	2,112	2,052	2,112	2,052
N Groups	352	342	352	342
KP F			10.782	10.342
Weights	✓	✓	✓	✓
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the count of domestic groundwater wells that reported a failure that year in a DAUCO. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. All regressions are weighted by the DAUCO crop acres \times # of Domestic Wells and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

Table E4: Impact of Surface Water Scarcity and Heat on Groundwater Outcomes: Using an Alternative 29° Celsius Threshold

Dependent Variable:	IV			CF/PPML
	(1) ΔDTW	(2) Well Failure	(3) New Ag Wells	(4)
Ag SW Deliveries (AF/ crop acre)	-2.829 (1.176)	-0.0531 (0.0181)	-12.29 (4.774)	-0.621 (0.274)
Degree Days >29C	0.0290 (0.00999)	0.00131 (0.000505)	0.0753 (0.0220)	0.00764 (0.00182)
Observations	560,931	468,081	9,996	8,680
Weights	Crop Acres # wells	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather	✓	✓	✓	✓

Note: The table presents the main specifications and outcomes of the paper, but instead uses a 29 degree Celsius threshold for extreme heat. Columns (1) -(3) are estimated using a linear IV model. Column (4) reports results from a control function and pseudo-Poisson maximum likelihood function with standard errors bootstrapped from 500 replications. All standard errors are clustered at the DAUCO level and are reported in parentheses.