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

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Abstract

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

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1 Introduction

The effects of climate change are projected to be large in magnitude and broad in reach (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005; Schlenker and Roberts, 2009; Dell, Jones, and Olken, 2012; Lobell, 2014; Graff Zivin and Neidell, 2014). Efforts to quantify the social costs of these climate effects must estimate not only the direct effects of weather shocks and the extent to which adaptation can reduce these damages (Barreca et al., 2016; Burke and Emerick, 2016), but also the cost of adaptation (Carleton et al., 2022; Hultgren et al., 2022). The possibility that adaptation by individuals may have social costs that differ from the private costs has been examined in the energy space but overlooked in other settings (Auffhammer and Aroonruengsawat, 2011; Davis and Gertler, 2015; Auffhammer, 2022; Colelli et al., 2022; Abajian et al., 2024b).[1] If adaptation has externalities, then current approaches may understate the full social costs of climate change. And since many negative externalities are already disproportionately borne by vulnerable groups (Banzhaf, Ma, and Timmins, 2019), the external costs of adaptation may constitute yet another way in which climate change exacerbates existing inequities (Carleton and Hsiang, 2016).

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

One important consequence of groundwater depletion is that it can harm access to drinking

[1] Heat-driven increases in energy consumption may lower private costs but impose external costs through increased carbon emissions (Auffhammer and Aroonruengsawat, 2011; Davis and Gertler, 2015; Auffhammer, 2022; Colelli et al., 2022). While energy use may increase in some locations, in other locations warming temperatures will decrease demand for cooling. At a global scale, climate change is expected to lead to decreased energy demand, and subsequently negative climate adaptation feedback (Rode et al., 2021; Abajian et al., 2024a).

water for rural households that rely on private groundwater wells for domestic purposes. Domestic wells tend to be shallower than agricultural wells, and therefore, more susceptible to failing (i.e., running dry) as groundwater tables fall. In California, domestic wells are also concentrated in disadvantaged communities comprised of low-income households and people of color.[2] Access to drinking water supplies among disadvantaged communities is a growing concern, and the links between environmental conditions, agricultural groundwater extraction, and domestic well failures remain unclear (Pauloo et al., 2020).

Our overall thesis is that farmers in California respond to heat and drought by increasing groundwater extraction, which harms access to drinking water in low-income and Latina/o communities. We build the case for this thesis through several steps of empirical analysis. First, we study how environmental conditions affect the outcomes that carry costs, showing that heat and surface water scarcity cause groundwater levels to decline more rapidly and domestic wells to fail more often. Then, we provide evidence that these damaging effects are due in part to adaptation actions taken by agricultural producers. Because data on groundwater extraction itself is unavailable, we focus on the extensive margin, showing that the construction of new agricultural wells speeds up in response to heat and water scarcity.[3] Finally, we argue that the remaining steps in the causal chain are mechanical, and we use known physical relationships to quantify the contribution of the extensive margin to overall damages.

Our empirical approach uses year-to-year variation that differs across locations to identify the effects of 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. Two-way fixed effects control for local fixed differences (such as historical water rights) and state-level shocks (such as recessions) that may affect water access and producer decisions.

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

[3]Ongoing work focuses on using electricity consumption to quantify the intensive-margin response attributable to weather shocks (Oehninger, Lawell, and Springborn, 2017; Hrozencik, Rouhi Rad, and Uz, 2023).

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 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 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 (AF) less than average—causes groundwater levels to fall by 2 ft more than usual in the same year. The effect of this one-year shock persists over time, with groundwater levels dropping an additional 19% more than usual in the subsequent three years. Heat exposure equal to average exposure in 2021—23 harmful degree days (HDD) more than average—causes groundwater levels to fall by 0.7 ft (8 in) more than usual.

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

After showing that environmental shocks harm groundwater levels and drinking water access, we turn to establishing a mechanism. Our third result is that both surface water scarcity and

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

extreme heat increase the number of new agricultural wells constructed. Contemporaneous surface water scarcity equivalent to the 2021 drought results in 320 additional new agricultural wells per year, a 32% increase in well construction relative to the usual pace. 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 link in the causal chain—how new wells affect groundwater depletion—we lay out a simple conceptual model that decomposes the observed effect on groundwater levels into three channels: the intensive margin response (extracting more per well), the extensive margin response (building more wells), and recharge. Using this model and our empirical estimates, we estimate that 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.

Our central contribution is to empirically illustrate a case in which adaptation to climate change can produce negative externalities that are quantitatively important. We argue the external costs of adaptation should be considered in both estimates of the social cost of carbon as well as the design of climate adaptation policy. The literature on climate impacts recently has made progress in quantifying the costs of adaptation in addition to the benefits (Schlenker, Roberts, and Lobell, 2013; Carleton et al., 2022; Hultgren et al., 2022), but adaptation is typically modeled as a choice involving only private tradeoffs. If agents adapt in part by offloading costs to other parties without their consent, as they do in our setting, then profit-maximizing behavior will result in *more* adaptation than is socially optimal. This is the case in Abajian et al. (2024b), which shows that catastrophic drought policies in Cape Town, South Africa led wealthier households to adopt private groundwater wells as a substitute for piped water, imposing fiscal and environmental externalities on other municipal water users. Relatedly, (Hsiao, 2024) shows that inequity in flood exposure can occur if richer households re-locate in response to climate shocks, pushing poorer households out of safer regions through rising housing prices. Our work complements these recent case studies, showing that across a large geographic range, agricultural users' response to frequent but severe surface water shortages imposes external costs within and across sectors. Our work suggests that an accounting of climate damages that ignores externalities will yield an over-optimistic view of the scope for adaptation and understate the costs of climate change.

Our results also bring empirical evidence to bear on how climate change will affect externalities induced by the open-access management of common pool resources. A longstanding literature documents that open-access conditions lead to too much extraction of groundwater at too quick a pace (Hotelling, 1931; Pfeiffer and Lin, 2012; Ayres, Meng, and Plantinga, 2021). Less clear is how climate change interacts with these externalities. Recent work on the water resource impacts of climate change have focused on the link between climate and irrigation, showing increases in irrigation as farmers seek to buffer against warming temperatures and more variable precipitation (Taraz, 2017; Taylor, 2023). Our findings show that the externalities from groundwater consumption are exacerbated by the types of environmental conditions likely to worsen under climate change, increasing the value of sound resource management.[5] In short, groundwater management policy is climate adaptation policy.

Finally, this paper also adds a new dimension to our understanding about inequities in exposure to environmental costs (Banzhaf, Ma, and Timmins, 2019). A recent literature documents that disadvantaged communities bear a disproportionate burden of pollution and seeks to identify the distributional implications of environmental regulations intended to reduce pollution (Cain et al., 2023). This work highlights trends in pollution disparities over time and decomposes the relative contribution of command-and-control and market-based approaches in explaining changes in this gap (Fowlie, Holland, and Mansur, 2012; Bento, Freedman, and Lang, 2015; Shapiro and Walker, 2021; Hernandez-Cortes and Meng, 2023). Less is known about the equity implications of an open-access management regime, which governs many common-pool resources.[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.

2 Agriculture and Water in California

The context we study is California, a setting where agriculture accounts for 80% of consumptive use, droughts are increasingly frequent and severe, and access to reliable drinking water supplies poses a concern in many rural communities. California is a leading producer of agricultural products in the U.S. and globally, comprising over a third of the nation's vegetables and almost three-quarters of its fruits and nuts (California Department of Food and Agriculture, 2020). One reason

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

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

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 and Lower Colorado River Project comprise the three main surface water projects. Water contracts specify a maximum annual volume of water supplied and a contract priority. This array of water rights and water projects dates back more than 40 years and created an entitlement system where neighboring water districts obtain surface water from different sources under different contract conditions.

Within an irrigation district, large fluctuations exist in yearly water project deliveries. Each year the government agency managing a water project announces allocation percentages for each contract type. These percentages are based on reservoir levels, environmental conditions and

[7] Most agricultural water rights and contracts are held by irrigation districts – local government agencies – which then supply water to farms within their jurisdictions. Within each district, water is typically rationed by quantity rather than price, and by custom or law water is distributed uniformly to producers on a per-acre basis.

weather and determine how much of the maximum volume an irrigation district receives. Allocation percentages are announced in advance of planting decisions and are largely based on winter precipitation and reservoir levels. There are 13 different contract types, where the allocation percentage a district receives differs based on the water project and priority order. As a result, within a year different districts receive different allocation percentages, depending on the contract type and their appropriative water rights.

The actual surface water deliveries that a district receives can differ from allocations in a few ways. Irrigation districts can purchase additional water mid-season on the spot market, 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 droughts, 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 San Joaquin Valley of California groundwater levels in some basins have experienced over a 100 foot reduction in the past 10 years (Department of Water Resources, n.d.). Partly in response to these concerns, in 2014 California passed historic groundwater regulation - the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater by 2042.[8]

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.

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

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 wells (California State Board of Equalization, 2023). They also are drilled with a wider diameter than residential wells to allow for higher flow rates. Modern material and construction of wells allows for their lifespan to often exceed 100 years. New wells are required to be reported to the state Department of Water Resources (DWR) and are typically constructed in under a week (Central Valley Flood Protection Board, 2020).

Drinking Water in Rural Communities

Most individuals in California receive residential and drinking water from community water systems, but many rural communities obtain drinking water directly and exclusively from private domestic wells.[9] Private domestic well users draw groundwater from aquifers that are shared with agricultural users. Compared with agricultural wells, domestic wells are typically shallower and therefore more susceptible to failing, or running dry, as groundwater tables decline. Dry wells impose substantial costs on households, either through the costly construction of new, deeper wells or the regular purchasing of alternative water sources, like bottled water.[10]

Private domestic wells are concentrated in agricultural regions of California and the San Joaquin Valley in particular (see Figure A1). These areas also comprise some of the most economically and socially vulnerable communities in California (see Figure A2). Populations in the San Joaquin Valley are 50.2% Hispanic (compared to a national average of 18.9%) and 23.2% of households are below the federal poverty line (compared to a national average of 12.9%). Further disparities exist within the domestic well-owning population. Figure 1 illustrates that 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

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

[10] Deteriorating drinking water quality is also a concern for many of these users, especially since these water sources are outside the jurisdiction of the Safe Drinking Water Act.

well failures are concentrated in relatively low income, rural and non-white communities.

Impacts of Climate Change in California

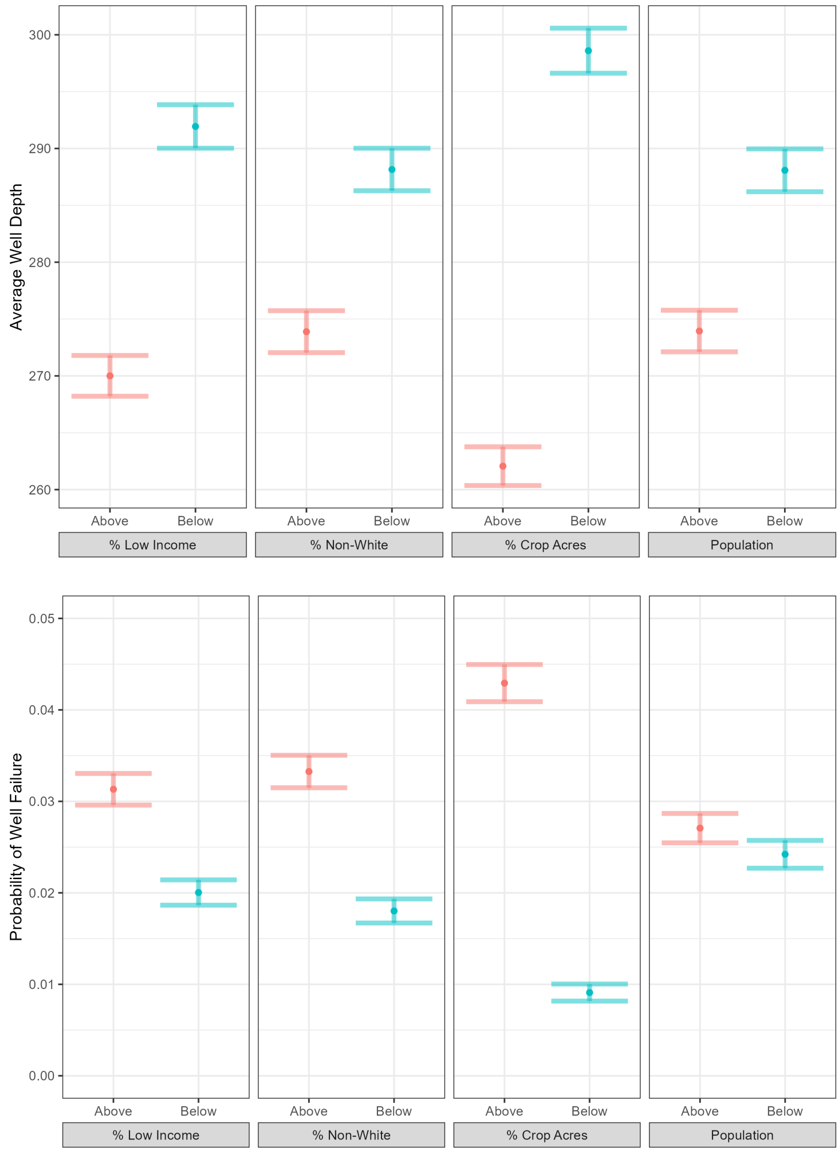
Water scarcity in California is expected to be exacerbated by climate change. While climate models project only modest changes in the mean annual precipitation, the amount of water available in reservoirs and canals for irrigation is projected to be reduced by 25% by 2060 (Wang et al., 2018). The latter is partly due to increased precipitation volatility and insufficient infrastructure to conserve water in reservoirs in the wettest years (Diffenbaugh, Swain, and Touma, 2015; Swain et al., 2018). Warming temperatures also increase crop demands for water. The implication of this is that even if surface water supplies do not change, extreme heat will lead farmers to demand more water for irrigation (Rosa et al., 2020).

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

3 Conceptual Model

We develop a conceptual framework based in physics to clarify the relationships between farmers' responses to heat and surface water, groundwater levels, and access to drinking water. This framework will later enable us 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 model and then introduce a time element since the decision to drill a well is inherently dynamic.

Figure 1: Domestic Well Depth and Failure Probability by Local Demographics



Note: Figure displays the mean well depth 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.

3.1 Contemporaneous Model

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

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

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

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

which depends on the starting depth to the water table DTW_0, consumption, and recharge. The effect of one AF of consumption 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.[11]

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

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

First, farmers may drill new irrigation wells and pump from them (the extensive margin): $\frac{\partial w}{\partial s}(s,h)$. Second, farmers may extract more groundwater from existing wells (the intensive margin): $\frac{\partial q}{\partial s}(s,h)$. Third, recharge is affected, $\frac{\partial R}{\partial s}(s,h)$, since if less total irrigation water is applied to cropland, less water drains through the soil into the aquifer below.[12]

[11] Groundwater aquifers are porous rock and sediment formations that store groundwater. The volume of water an aquifer can hold varies depending on porosity and sediment type. For highly porous aquifers, less total area is required to hold the same amount of water relative to a less porous aquifer. κ captures the inverse of storativity, a physical property of an aquifer. For an unconfined aquifer like much of the Central Valley, storativity is also equivalent to specific yield, which measures the proportion of space that water can occupy within an aquifer. As an example, a storativity value of 0.12, which is typical in California's Central Valley Aquifer (Department of Water Resources, 2020), indicates that 12% of the volume of the aquifer can hold water. The other 88% is composed of porous rock and sediment.

[12] For a heat shock, recharge also falls because heat increases evaporation, meaning that less of the applied water

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

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

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

3.2 Dynamic Framework

A limitation with the static model is that the decision to drill a well is dynamic. Contemporaneous weather shocks impact current and future well drilling, and well drilling decisions have persistent impacts on groundwater consumption. We now extend our framework to allow contemporaneous weather shocks to enter into current and future drilling decisions, and current drilling decisions to affect future groundwater extraction.[13]

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 $\mathbf{s}_\tau$ is a vector of current and past weather shocks at time τ.[14] 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 :

makes its way into the aquifer.

[13]Drilling decisions also depend on the current stock of wells, the option value from having a well, and expectations about future weather. Our modelling of the decision to drill a well focuses exclusively on contemporaneous and past weather realizations.

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

$$
\begin{aligned}
w_\tau(\mathbf{s}_\tau) &= w_{\tau-1} + \Delta w_\tau(\mathbf{s}_\tau) \\
&= w_0 + \sum_{\mu=1}^{\tau} \Delta w_\mu(\mathbf{s}_\mu)
\end{aligned} \tag{5}
$$

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

$$
\begin{aligned}
DTW_T(\mathbf{s_T}) &= DTW_0 + \kappa \sum_{\tau=t}^{T} C_\tau(\mathbf{s}_\tau) - \kappa \sum_{\tau=t}^{T} R_\tau(s_\tau) \\
&= DTW_0 + \kappa \sum_{\tau=t}^{T} q_\tau(s_\tau) w_\tau(\mathbf{s}_\tau) - \kappa \sum_{\tau=t}^{T} R_\tau(s_\tau)
\end{aligned} \tag{6}
$$

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 only dependent on the current period shock.

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:[15]

$$
\begin{aligned}
\underbrace{\frac{dDTW_T}{ds_t}}_{\text{cumulative effect}} &= \kappa \Big[\underbrace{w_t(\mathbf{s_t}) \times \frac{dq_t(s_t)}{ds_t}}_{\substack{\text{contemporaneous} \\ \text{intensive margin}}} + \underbrace{q_t(s_t) \times \frac{\partial w_t(\mathbf{s_t})}{\partial s_t}}_{\substack{\text{contemporaneous} \\ \text{extensive margin}}} + \\
& \underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_t(\mathbf{s_t})}{\partial s_t}}_{\substack{\text{future pumping} \\ \text{from wells drilled in } t}} + \underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_\tau(\mathbf{s}_\tau)}{\partial s_t}}_{\substack{\text{future drilled wells} \\ \text{from } s_t}} - \underbrace{\sum_{\tau=t}^{T} \frac{\partial R_\tau(\mathbf{s}_\tau)}{\partial s_t}}_{\text{recharge}} \Big].
\end{aligned} \tag{7}
$$

[15] More detailed steps of this decomposition can be found in Appendix Section A.1

Table 1: Summary Statistics

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

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

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, $\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_\tau(\mathbf{s}_\tau)}{\partial s_t}$. Fifth, weather shocks will have contemporaneous and future effects on recharge: $\sum_{\tau=t}^{T} \frac{\partial R_\tau}{\partial s_t}(\mathbf{s}_\tau)$.

Our conceptual model provides a framework to quantify the magnitude of each margin in explaining weather-induced changes in groundwater availability, and we use it to calculate the long-run effects of well construction on groundwater extraction.

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 2 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 weather-induced reductions in surface water availability. Adjacent water districts can receive very different allocations, and these differences in allocations vary year to year.

Depth to the Water Table

Monitor level measures of the depth to the water table are available from over 20,000 monitoring wells on average between 1993 and 2020. Depth to the water table measures come from two sources: the State Water Resources Control Board's Groundwater Information System and DWR's Periodic Groundwater Level Measurement.[19] Within each monitor-year, we select a single date to

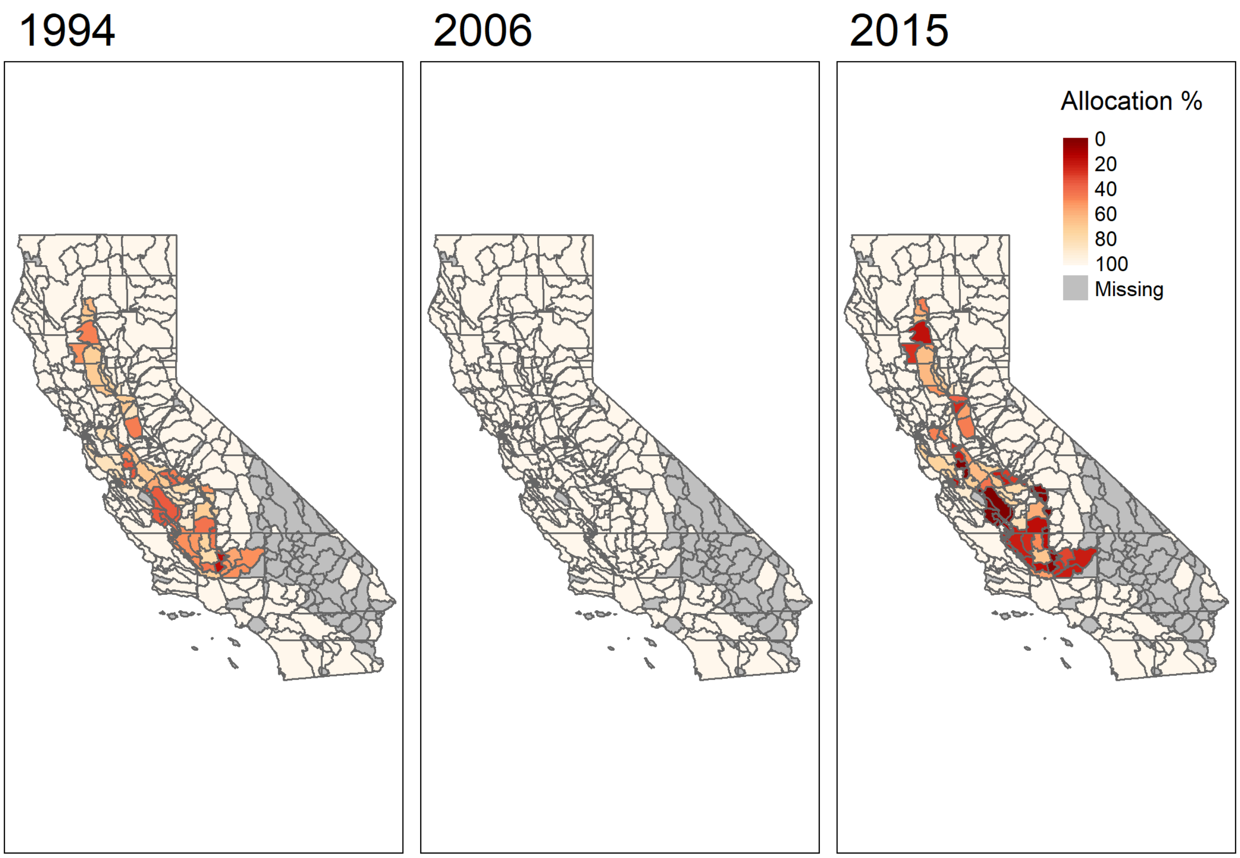
[16]Surface water delivery data for the CVP are first available from the U.S. Bureau of Reclamation in a digitized format in 1993. Therefore, these variables determine the temporal length of our final panel for analysis.

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

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

[19]Figure A3 plots the location of each unique monitoring well in our sample and the boundaries of California's principle groundwater basins. This figures highlights that there is broad coverage of monitoring wells in the agricultural centers of California, such as the San Joaquin Valley.

Figure 2: Agricultural Surface Water Allocation Percentages



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

measure the depth to the water table. We choose the reading closest to March 15 of the subsequent year (e.g. March 15, 2016 to measure the 2015 end-of-year groundwater depth), since the water table at that point in time will reflect the cumulative effects of groundwater pumping and recharge in the preceding year. Year-to-year differences in monitor-level depth measure the change in the depth to the water table.[20]

As shown in Table 1, groundwater levels decline by approximately 4 inches per year on average. This statistic, however, masks substantial temporal and spatial heterogeneity in groundwater levels. Figure 3 illustrates the change in depth to the groundwater in each DAUCO in three different years. It makes clear that groundwater tables generally decline in the drought years 1994 and 2015, and replenish during wet years. Declines are most pronounced in location-years that experience the largest surface water curtailments, with some regions experiencing annual declines of over 10 feet.

Well Construction

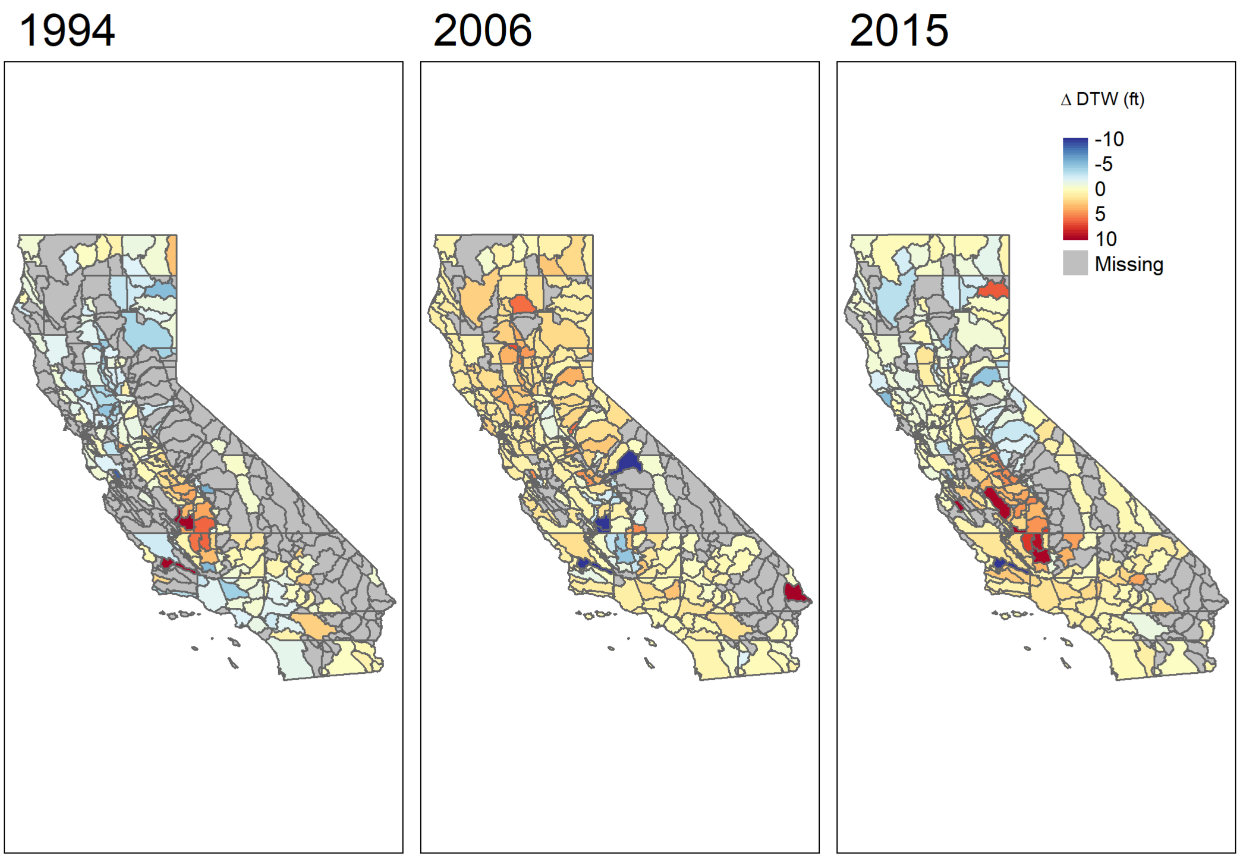
We measure the extensive-margin response to surface water scarcity and extreme heat through the metric of new agricultural well construction. We use the universe of Well Completion Reports from DWR, which reports each new well's location, the drilled well depth, intended use, and drilling date. These reports also contain a record of which wells were destroyed and their locations.[21] Our final outcome is the count of the total number of new agricultural irrigation wells per DAUCO-year. We also use the destruction records as an outcome in an alternative specification to test whether new well construction is offset by old well destruction.

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

[20]To reduce the influence of extreme values, we exclude observations where a year-to-year change is more than 1.5 times greater than the inner decile range reported from all monitoring wells in the same DAUCO over our sample. This rule removes observations with drastically different changes in groundwater levels than other local groundwater measures. Some of these outlier observations are the result of a misplaced decimal, while other errors occur from monitor errors, but we cannot easily distinguish the source of error in these data.

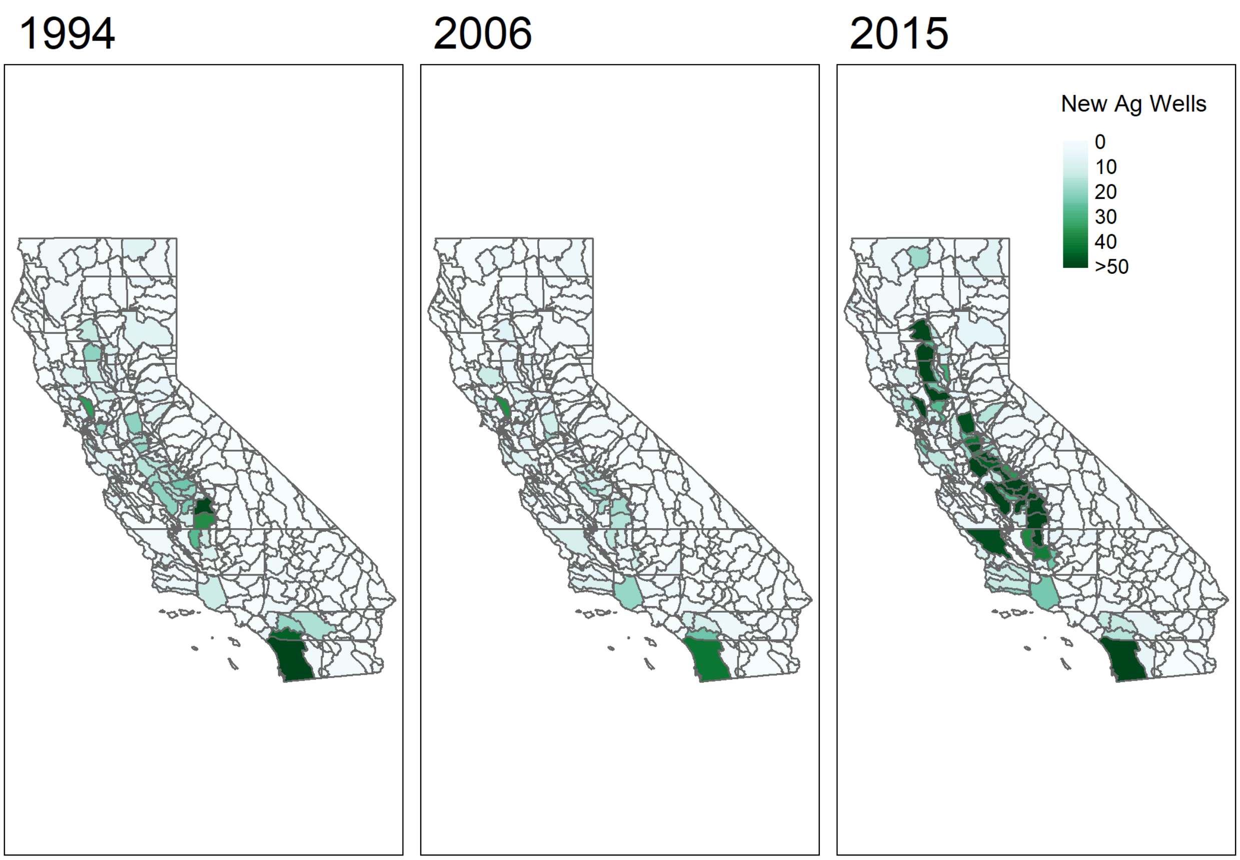
[21]Since 1949, the California Water Code requires that well drillers complete a Well Completion Report with the California DWR within 60 days of the well construction and/or destruction. Prior to 2015, all Well Completion Reports were handwritten and later digitized for the construction of this dataset.

Figure 3: Annual Changes in Depth to the Water Table



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

Figure 4: New Agricultural Well Construction



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

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. When wells are reported dry, county-led emergency services are notified to provide alternative water as a short-term solution. These data, shown on a map in Figure A4, contain the coordinates for the reported dry well, the date the issue started, and if the issue was resolved. Using the Well Completion Report data, we create a panel on the service status of all domestic wells by geographically matching the reported failures to the registered domestic wells. We denote a well-year as failed if a well failure is self-reported; otherwise we assume it is functional. This is an undercount of the true number of domestic well failures, since household reporting is voluntary. Still, it is an improvement over an approach that estimates failures based on the relationship between well depth and groundwater table height, which risks misclassifying wells for other reasons, e.g., 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 A4 illustrates that these well failures are concentrated in California's San Joaquin Valley. They also occur disproportionately in locations that experience large agricultural surface water curtailments.

Weather

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

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

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

$$HDD(T) = \begin{cases} 0 & \text{if } T \leq 32C \\ T-32 & \text{if } T > 32C \end{cases} \tag{9}$$

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

5 Empirical Model

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

Changes in Depth to the Water Table

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

$$\Delta DTW_{idt} = \beta_1 SWD_{dt} + \beta_2 HDD_{dt} + B' X_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt}. \tag{10}$$

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

Our two regressors of interest are SWD_{dt} and HDD_{dt}. SWD_{dt} measures surface water deliveries in AF per crop acre in DAUCO region d and year t. Similarly, HDD_{dt} is the annual number of harmful degree days in DAUCO d and year t. The vector X_{dt} measures precipitation and growing degree days; λ_t captures statewide annual shocks and trends; and α_i absorbs fixed well-level unobservables. Standard errors are clustered by DAUCO to account for serial correlation among wells within the same district.

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

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

$$\Delta DTW_{idt} = \sum_{\tau=1}^{b} \beta_{1\tau} SWD_{dt-\tau} + \sum_{\tau=1}^{b} \beta_{2\tau} HDD_{dt-\tau} + B' X_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt}. \tag{11}$$

All variables are defined as in equation (10), 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 $\tau = [\,1, b]$, where $\tau = 1$ corresponds to contemporaneous shocks and b denotes the number of annual lags in the model. This specification tests for contemporaneous, β_{11} and β_{21}, and persistent effects, $\beta_{1\tau}$ and $\beta_{2\tau}$ when $\tau \in \{2, b\}$, of environmental shocks. The cumulative effect of surface water and heat shocks on groundwater levels over time horizon b is given by $\sum_{\tau=1}^{b} \beta_{1\tau}$ and $\sum_{\tau=1}^{b} \beta_{2\tau}$.

Instrumental Variables Model

Of the two treatment variables in equation (10), HDD_{dt} is likely exogenous, conditional on well and year fixed effects and other measures of local weather. However, SWD_{dt} is not, since irrigation districts can influence their own surface water deliveries. For example, in a drought year, a district may purchase additional surface water, while its farmers also extract more groundwater in drought years. We therefore instrument for deliveries using surface water allocations, which are set ahead of the growing season based on environmental conditions and cannot be influenced by farmers or local officials. The exclusion restriction likely holds, since allocations are unlikely to be related to other determinants of local groundwater demand: Allocations are set based on precipitation conditions occurring in the mountainous regions during the rainy season, while groundwater demand occurs in agricultural valleys during the summertime. Still, to rule out a possible correlation between local weather and allocations, we include precipitation as a control variable in our full specifications.

Our initial specification is the following model:

$$\begin{aligned} \Delta DTW_{idt} &= \beta_1 S\hat{W}D_{dt} + \beta_2 HDD_{dt} + B' X_{idt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\ SWD_{dt} &= \gamma_1 SWA_{dt} + \gamma_2 HDD_{dt} + \Gamma' X_{idt} + \lambda_t + \alpha_i + \mu_{idt}, \end{aligned} \tag{12}$$

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

Domestic Well Failures

Changes in the depth to the groundwater table may cause domestic wells to run dry. To estimate the effect of heat and surface water scarcity on domestic well failures, we use well-level panel data and again estimate an instrumental variables model with two-way fixed effects using two-stage least squares:

$$
\begin{aligned}
Y_{idt} &= \beta_1 S\hat{W}D_{dt} + \beta_2 HDD_{dt} + B'X_{dt} + \lambda_t + \alpha_i + \varepsilon_{idt} \\
SWD_{dt} &= \gamma_1 SDA_{dt} + +\gamma_2 HDD_{dt} + \Gamma' X_{dt} + \lambda_t + \alpha_i + \mu_{idt}.
\end{aligned} \tag{13}
$$

The outcome, Y_{idt}, is now a binary variable indicating whether domestic well i reported failing in year t. All other variables are defined as in equation (12), with the exception of α_i which denotes domestic well fixed effects. The coefficients of interest, β_1 and β_2, represent the change in likelihood that a domestic well fails in a given year resulting from changes in surface water availability and extreme heat, respectively. The regressions are weighted by the number of crop acres in the DAUCO. Standard errors are clustered at the DAUCO level.

Agricultural Well Construction

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

$$
\begin{aligned}
E[Y_{dt} | SWD_{dt}, HDD_{dt}, \mathbf{X}_{dt}, \alpha_d, \lambda_t] &= \exp\{\beta_1 SWD_{dt} + \beta_2 HDD_{dt} + B'X_{dt} + \alpha_d + \lambda_t + \phi \hat{\mu}_{dt}\} \\
SWD_{dt} &= \gamma_1 SDA_{dt} + \gamma_2 HDD_{dt} + \Gamma' X_{dt} + \alpha_d + \lambda_t + \mu_{dt}.
\end{aligned} \tag{14}
$$

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.[22] Poisson

[22] This intuition is an informal generalization of the case of a binary variable and two periods, formalized by

regression is also arguably more appropriate for non-negative count data, and it may be more efficient given the variable's right skew (see Figure A5 for a histogram). For robustness, we also report results using linear two-stage least squares.

6 Results

Damages: Groundwater Depletion and Well Failures

Table 2 reports results for the change in the groundwater depth from the two-way fixed effects and instrumental variables models described in equations (10) and (12). Columns (1) and (2) display the reduced-form effects of surface water allocations, without and with extreme heat and local weather controls. Columns (3) and (4) display results in which allocations serve as an instrument for surface water deliveries.

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

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

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).

[23]For additional historical context on the size of typical shocks, we calculate the sample "within" standard deviation by computing the standard deviation of surface water and heat for each DAUCO across time, and taking the average across DAUCOs. A one "within" standard deviation change is equal to 0.54 AF/acre for surface water and 14 HDD for extreme heat.

Table 2: Changes in Depth to the Groundwater

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/acre)	-1.967	-1.533		
	(0.674)	(0.636)		
Ag SW Deliveries (AF/acre)			-3.684	-2.914
			(1.196)	(1.174)
Harmful Degree Days		0.0308		0.0309
		(0.0160)		(0.0115)
Observations	561,085	560,931	561,085	560,931
N Groups	83,782	83,762	83,782	83,762
Weights	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. Columns (1) and (2) report results from the reduced-form OLS model. Columns (3) and (4) report the second-stage IV results, where 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 DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

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

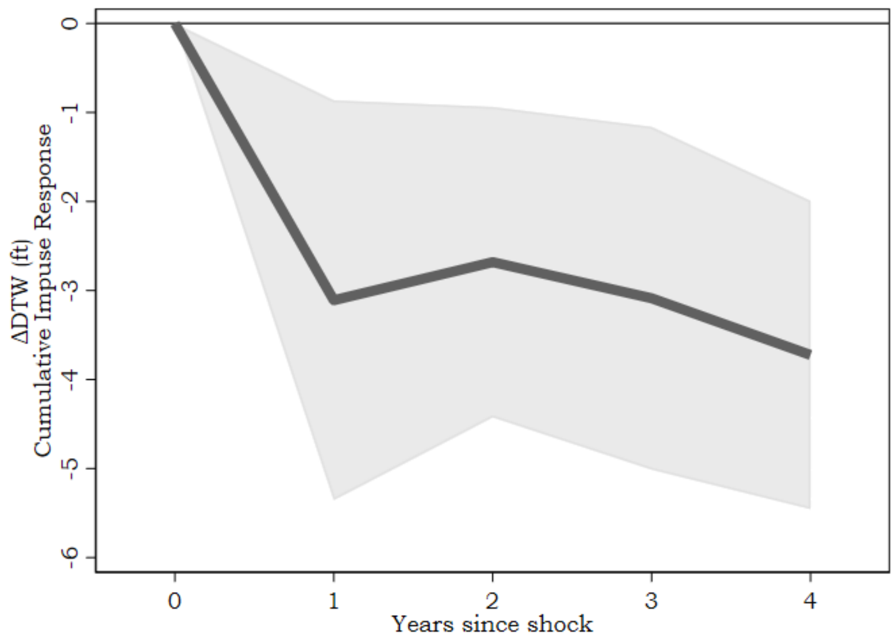
Having identified the contemporaneous effect, we next seek to estimate the cumulative effect of surface water shocks on groundwater stocks, as captured by $\frac{dDTW_T}{ds_t}$ in equation (8). To estimate the cumulative effect, we first need to choose a time horizon T for the distributed lag model presented in equation (11). 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 A5) to estimate the cumulative effect of surface water shocks on groundwater levels for the four years since the shock. If surface water scarcity affects groundwater depletion for more than four years following the initial shock, we will understate the cumulative effect.

Figure 5 plots the cumulative effect (i.e., the sum of contemporaneous and lagged coefficients) of a 1-AF/ac surface water shock on the depth to the water table in each of the four years following the surface water curtailment. Table A5 reports annual effects of surface water shocks and harmful degree days over a four year lag. Figure A6 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. The pattern in Figure 5 indicates that surface water scarcity causes the greatest decline in groundwater stocks in the year in which it occurs, 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 contemporaneous (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. These lagged effects represent the difference between the cumulative and contemporaneous effects, so following equation (8), we interpret this effect as the future margin of response.

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 percentage points, and a one AF/acre reduction in surface water increases well failures by 5 percentage points. Translated to our 2021 example, well failure probability increased by 3.4 percentage points as a result of surface water curtailments and by 4.8 percentage points due to extreme heat. These

Figure 5: 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.

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.[24] 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)

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

Table 3: Linear Probability of Reported Well Failure

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

Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. Column 5 reports results from the subset of counties within the California Partnership for the San Joaquin Valley. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

highlight that even within a sample of counties that receive similar state assistance, our results are unchanged.

We find that weather-driven well failures are concentrated almost exclusively among well-owners that are lower-income populations and among well-owners of color. To investigate the distributional effects of well failures, we decompose the treatment effects reported in column (4) of Table 3 by estimating separate regressions that interact the outcome variable with subgroup indicators.[25] While domestic wells are disproportionately located in low income areas and communities of color, we define sub-groups such that there are an equal number of domestic wells in each group. Panels (a) and (c) of Figure 6 plot the effects for surface water curtailments and

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

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, treatment effects occur disproportionately among relatively low-income and non-white domestic well users. As shown in Figure 1, this disproportionate change is likely driven by the fact that wells in these subgroups are drilled at statistically shallower depths. Relatively whiter well-owning households exhibit almost no change in domestic well failures, and higher-income populations demonstrate only a small increase in well failures.

One Mechanism: Agricultural Well Construction

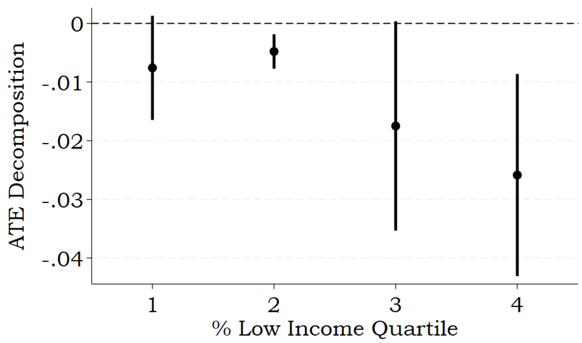
Our results so far establish that heat and surface water scarcity cause damages in the form of groundwater depletion and domestic well failures. Our goal now is to demonstrate that these damages are at least in part due to adaptation by agricultural producers. To do so, we first estimate the effects 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 A4 provides the reduced-form results of well construction regressed directly on the allocations instrument.

Our third main result is that heat and surface water scarcity induce farmers to construct more agricultural wells. Farmers drill approximately 46.2% more agricultural wells for a 1-AF/acre reduction in surface water and 1.3% more for every 1-HDD increase.[26] 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 A2 evaluates the effect of surface water and temperature shocks on the drilled depth of newly constructed wells. Wells appear to be drilled deeper in response to heat and water scarcity, though these estimates are imprecise.

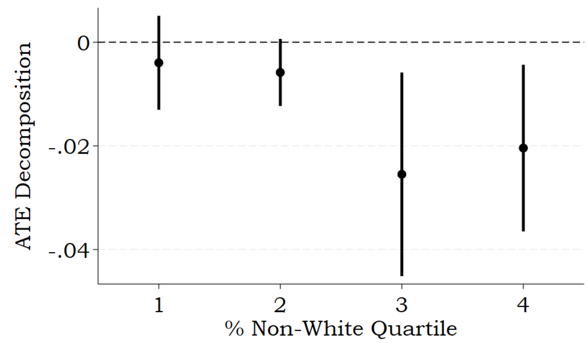
One potential threat to interpreting these results as a mechanism of groundwater depletion

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

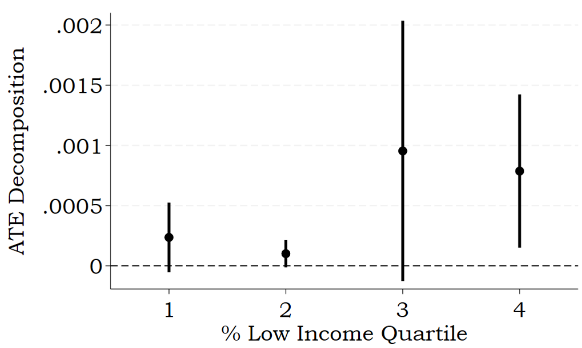
Figure 6: Decomposing Average Treatment Effects (ATE) by Local Demographics



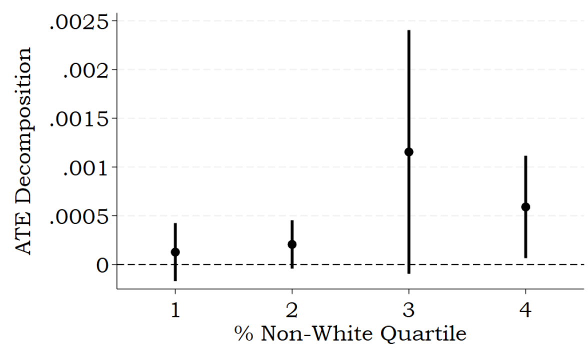
(a) Ag SW Deliveries (AF/acre)



(b) Ag SW Deliveries (AF/acre)



(c) Harmful Degree Days



(d) Harmful Degree Days

Note: Figure shows the share of the treatment effect on surface water and heat by demographic quartile (i.e. treatment effects for the four groups sum to pooled treatment effect in Table 3). Dependent variable is a binary outcome if a domestic groundwater reported a failure that year multiplied by demographic quartile identifiers. For panels (a) and (c), the treatment effect on well failures is decomposed by the Census tract quartile for the percent of the population that is low-income. In panels (b) and (d), the treatment effect is decomposed by quartiles of the percent of the population that is non-white. All regressions are weighted by the DAUCO crop acres, include year and DAUCO fixed effects, and control for local weather.

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

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

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

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

To introduce dynamics into the well drilling decision and probe the possibility that 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. 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 a series of past and contemporaneous shocks, then past and current negative shocks may induce farmers to construct more wells. This would be captured by 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 should take the opposite sign of the contemporaneous effect because drilling a well today offsets the need to drill one in the future. While our specification does not allow us to decompose the two channels, we can examine the gross effect of lagged shocks on well construction.

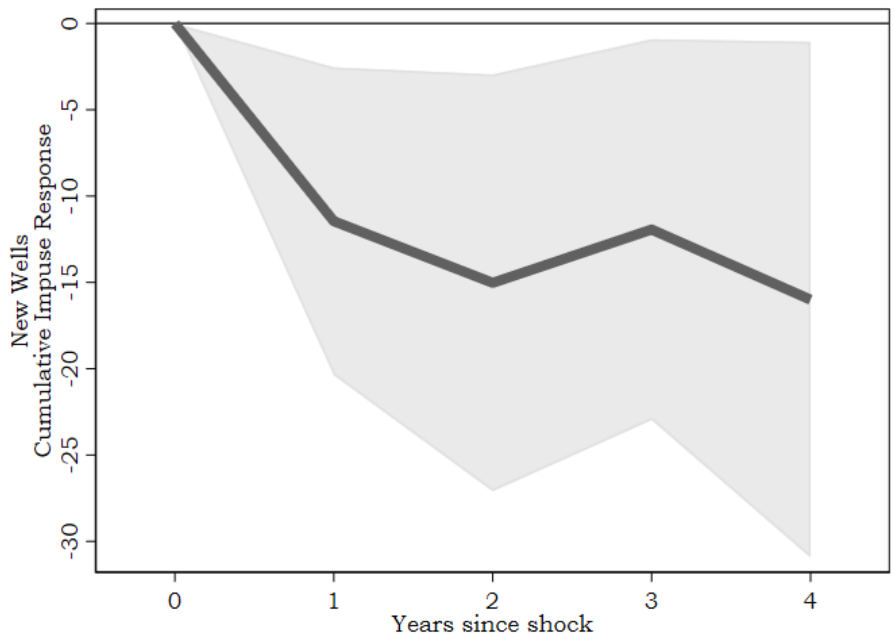
Figure 7 plots the cumulative effect of a 1-AF/ac surface water shock on new well construction in each of the four years following the surface water curtailment, and Table A6 reports individual annual effects in a stepwise fashion.[27] Incorporating lagged surface water deliveries increases the extensive-margin 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. 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 the mechanism of well construction. To answer this question, we proceed in two steps. First, we apply the simple contemporaneous physical model from Equation (3) to decompose the effect on groundwater depth into three margins: (1) the contemporaneous extensive margin of well construction, (2) the intensive margin of increased pumping per well, which is unobserved, and (3) changes in recharge rates. Using effects recovered from this static decomposition, we then apply the dynamic

[27]Figure A7 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 (14) is incompatible with lagged variables that enter nonlinearly.

Figure 7: 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.

model from Equation (8); this augments the decomposition to include the future well drilling margins.

Table A7 lists the parameter values we use for this exercise. They include (a) our point estimates on the change in groundwater depth and new well construction, (b) one parameter that we obtain directly from our raw data, the count of existing wells w, and (c) three parameters that we calibrate from the literature specific to California: average annual groundwater extraction per well (q_{tau}), aquifer storativity (κ^{-1}), and the recharge rate ($\sum_{\tau=t}^{T} \frac{\partial R_\tau(\mathbf{s}_\tau)}{\partial s_t}$).[28] Where multiple published values are plausible, we choose conservative values that will reduce the size of the extensive margin relative to the other mechanisms.

[28]This 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 a while to percolate through the ground into the aquifer.

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. A problem with this static decomposition is that new wells constructed in a given year can only affect groundwater extraction in that year.

We now extend our framework to allow past water shocks to have lasting impacts on well construction, and new well construction to have persistent effects on groundwater extraction. As shown in equation (8), the marginal effect of weather shocks on groundwater depth can now be decomposed into five mechanisms: (1) pumping more from each well (the contemporaneous intensive margin), (2) constructing new wells that pump more today (the contemporaneous extensive margin), (3) the future increase in pumping from new wells constructed today, (4) the future increase in well construction from surface water shocks today and (5) recharge (contemporaneous and future effects). Of the five mechanisms, we already know three from the static decomposition above; 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.[29] 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

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

them:

$$\frac{dDTW_T}{ds_t} - \frac{dDTW_t}{ds_t} = \kappa \Big[\underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_t(\mathbf{s_t})}{\partial s_t}}_{\substack{\text{future pumping} \\ \text{from wells drilled in } t}} + \underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_\tau(\mathbf{s}_\tau)}{\partial s_t}}_{\substack{\text{future drilled wells} \\ \text{from } s_t}} \Big] = \sum_{\tau=t+1}^{T} \frac{dDTW_\tau}{ds_t}. \tag{15}$$

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/ac is a 0.45 AF/ac decline in groundwater stocks. Of this depletion, 40% is attributable to lost recharge, leaving a 0.26 AF/ac 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 or 25% of the total effect, is attributable to the contemporaneous and future well-drilling margins.[30]

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

7 Conclusion

Groundwater serves as a critical natural resource that must meet the needs of the environment, the agricultural industry, and millions of residential households in California. Using well-level data spanning almost three decades, this paper shows that climate change has accelerated groundwater

[30] The 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 7 and Table A6, we know that new well construction increases about 31% more beyond the initial year from the sum of the lagged response ($\frac{-16.07 - -12.38}{-12.38}$).

depletion and exacerbated existing externalities. We demonstrate that this is driven in part by additional extraction by farmers as they rely more heavily on groundwater to mitigate surface water scarcity and extreme heat. This adaptation behavior limits the private costs of weather fluctuations to agricultural users in the near term, but imposes external costs on domestic well owners. Importantly, these external costs are heavily born by people of color and low-income households.

The findings from this study are directly relevant to the management of groundwater, which is largely unregulated across the world. Myriad collective action governance, restrictions, and markets have been recently proposed or enacted as solutions to manage groundwater with some success (Ayres, Meng, and Plantinga, 2021; Burlig, Preonas, and Woerman, 2021; Earnhart and Hendricks, 2023; Bruno and Hagerty, 2023; Bruno, Jessoe, and Hanemann, 2024). Restrictions or moratoria on new well drilling, especially in drought years, are another potential regulatory instrument to curb groundwater depletion (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; Auffhammer, 2018; Hultgren et al., 2022). Long-run costs may be reduced if agricultural producers adopt new technologies, change the location and types of crops grown, or adjust the quantity and composition of inputs (Sloat et al., 2020; Rosa et al., 2020; Aglasan et al., 2023). But the open-access management of a common-pool resource may result in the opposite being true. We show that in the short-run, heat and surface water shocks will deplete the available groundwater stock, suggesting that in the long-run the costs of climate change may be amplified if farmers cannot rely on groundwater to buffer against these shocks (Hornbeck and Keskin, 2014; Perez-Quesada, Hendricks, and Steward, 2023).

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

References

Abajian, A., T. Carleton, K.C. Meng, and O. Deshenes. 2024a. "The Climate Adaptation Feedback." *Working Paper*, pp. .

Abajian, A., C. Cole, B.K. Jack, K.C. Meng, and M. Visser. 2024b. "Dodging Day Zero: Drought, Adaptation, and Inequality in Cape Town." *Working Paper*, pp. .

Aglasan, S., R.M. Rejesus, S. Hagen, and W. Salas. 2023. "Cover Crops, Crop Insurance Losses, and Resilience to Extreme Weather Events." *American Journal of Agricultural Economics* Forthcoming.

Auffhammer, M. 2022. "Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption." *Journal of Environmental Economics and Management* 114:102669.

—. 2018. "Quantifying Economic Damages From Climate Change." *Journal of Economic Perspectives* 32(4):33–52.

Auffhammer, M., and A. Aroonruengsawat. 2011. "Simulating the impacts of climate change, prices and population on California's residential electricity consumption." *Climatic change* 109:191–210.

Ayres, A.B., K.C. Meng, and A.J. Plantinga. 2021. "Do Environmental Markets Improve on Open Access? Evidence from California Groundwater Rights." *Journal of Political Economy* 129:2817–2860.

Banzhaf, S., L. Ma, and C. Timmins. 2019. "Environmental Justice: The Economics of Race, Place, and Pollution." *Journal of Economic Perspectives* 33(1):185–208.

Barreca, A., K. Clay, O. Deschênes, M. Greenstone, and J.S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the U.S. Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy* 124:105–159.

Bento, A., M. Freedman, and C. Lang. 2015. "Who Benefits from Environmental Regulation? Evidence from the Clean Air Act Amendments." *The Review of Economics and Statistics* 97:610–622.

Blanc, E., and W. Schlenker. 2017. "The Use of Panel Models in Assessments of Climate Impacts on Agriculture." *Review of Environmental Economics and Policy* 11:258–279, Publisher: The University of Chicago Press.

Brozović, N., D.L. Sunding, and D. Zilberman. 2010. "On the Spatial Nature of the Groundwater Pumping Externality." *Resource and Energy Economics* 32:154–164.

Bruno, E., and N. Hagerty. 2023. "Anticipatory Effects of Regulation in Open Access." *Working Paper*, pp. 1–48, Montana State University, `https://hagertynw.github.io/webfiles/Anticipatory_Effects_of_Regulation.pdf`.

Bruno, E., K.K. Jessoe, and W.M. Hanemann. 2024. "The Dynamic Impacts of Pricing Groundwater." *Journal of the Association of Environmental and Resource Economists*, pp. , Forthcoming.

Burke, M., and K. Emerick. 2016. "Adaptation to Climate Change: Evidence from US Agriculture." *American Economic Journal: Economic Policy* 8:106–140.

Burlig, F., L. Preonas, and M. Woerman. 2021. "Energy, Groundwater, and Crop Choice." *Working Paper*, pp. 1–70.

Cain, L., D. Hernandez-Cortes, C. Timmins, and P. Weber. 2023. "Recent Findings and Methodologies in Economics Research in Environmental Justice.", pp. 1–42. CESifo Working Paper: `https://www.cesifo.org/en/publications/2023/working-paper/recent-findings-and-methodologies-economics-research-environmental`.

California Department of Food and Agriculture. 2020. "California Agricultural Statistics Review 2019-2020." `https://www.cdfa.ca.gov/Statistics/PDFs/2020_Ag_Stats_Review.pdf`.

California State Board of Equalization. 2023. "California Assessors Handbook." Section 534.62.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R.E. Kopp, K.E. McCusker, I. Nath, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *The Quarterly Journal of Economics* 137:2037–2105.

Carleton, T.A., and S.M. Hsiang. 2016. "Social and economic impacts of climate." *Science* 353:aad9837.

Central Valley Flood Protection Board. 2020. "Well Drilling Costs." http://cvfpb.ca.gov/wp-content/uploads/2020/11/8b.-EIS-Attachment-Well-Drilling-Costs.pdf.

Chen, J., and J. Roth. 2023. "Logs with Zeros? Some Problems and Solutions." *The Quarterly Journal of Economics* 139:891–936.

Colelli, F.P., J. Emmerling, G. Marangoni, M.N. Mistry, and E. De Cian. 2022. "Increased energy use for adaptation significantly impacts mitigation pathways." *Nature communications* 13:4964.

Davis, L.W., and P.J. Gertler. 2015. "Contribution of air conditioning adoption to future energy use under global warming." *Proceedings of the National Academy of Sciences* 112:5962–5967.

Dell, M., B.F. Jones, and B.A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence From the Last Half Century." *American Economic Journal: Macroeconomics* 4:66–95.

Department of Water Resources. n.d. "California Groundwater Live: Groundwater Levels." https://storymaps.arcgis.com/stories/b3886b33b49c4fa8adf2ae8bdd8f16c3.

—. 2020. "California's Groundwater Update 2020 Appendix C: Methods and Assumptions." https://data.cnra.ca.gov/dataset/calgw_update2020/resource/a1015683-7bc5-440b-8100-b58e51a21335.

Deschênes, O., and M. Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review* 97:354–385.

Diffenbaugh, N.S., D.L. Swain, and D. Touma. 2015. "Anthropogenic Warming Has Increased Drought Risk in California." *Proceedings of the National Academy of Sciences* 112:3931–3936.

Earnhart, D., and N.P. Hendricks. 2023. "Adapting to Water Restrictions: Intensive Versus Extensive Adaptation Over Time Differentiated by Water Right Seniority." *American Journal of Agricultural Economics* n/a.

Edwards, E.C. 2016. "What Lies Beneath? Aquifer Heterogeneity and the Economics of Groundwater Management." *Journal of the Association of Environmental and Resource Economists* 3:453–491.

Edwards, E.C., and T. Guilfoos. 2021. "The Economics of Groundwater Governance Institutions across the Globe." *Applied Economic Perspectives and Policy* 43:1571–1594.

Fowlie, M., S.P. Holland, and E.T. Mansur. 2012. "What do Emissions Markets Deliver and to Whom? Evidence from Southern California's NOx Trading Program." *American Economic Review* 102:965–993.

Gailey, R.M., J.R. Lund, and J. Medellín-Azuara. 2019. "Domestic well reliability: evaluating supply interruptions from groundwater overdraft, estimating costs and managing economic externalities." *Hydrogeology Journal* 27:1159–1182.

Graff Zivin, J., and M. Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32:1–26.

Hagerty, N. 2021. "Adaptation to Water Scarcity in Irrigated Agriculture." *Working Paper*, pp. 1–73, Montana State University, `https://hagertynw.github.io/webfiles/Surface_Water_Adaptation.pdf`.

Hernandez-Cortes, D., and K.C. Meng. 2023. "Do Environmental Markets Cause Environmental Injustice? Evidence from California's Carbon Market." *Journal of Public Economics* 217:104786.

Hornbeck, R., and P. Keskin. 2014. "The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaptation to Groundwater and Drought." *American Economic Journal: Applied Economics* 6:190–219.

Hotelling, H. 1931. "The Economics of Exhaustible Resources." *Journal of Political Economy* 39:137–175.

Hrozencik, R.A., M. Rouhi Rad, and D. Uz. 2023. "Electricity Demand by the Irrigated Sector in Response to Climatic Shocks.", pp. .

Hsiao, A. 2024. "Sea Level Rise and Urban Inequality." *AEA Papers and Proceedings* 114:47–51.

Hultgren, A., T. Carleton, M. Delgado, D.R. Gergel, M. Greenstone, T. Houser, S. Hsiang, A. Jina, R.E. Kopp, S.B. Malevich, K.E. McCusker, T. Mayer, I. Nath, J. Rising, A. Rode, and J. Yuan. 2022. "Estimating Golobal Impacts to Agriculture from Climate Change Accounting for Adaptation." *SSRN*, pp. , `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4222020`.

Kuwayama, Y., and N. Brozović. 2013. "The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams." *Journal of Environmental Economics and Management* 66(2):364–382.

Lemoine, D. 2023. "Estimating the Consequences of Climate Change from Variation in Weather." Working Paper No. 25008, National Bureau of Economic Research, November.

Lobell, D. 2014. *Climate Change 2014-Mitigation of Climate Change: Summary for Policymakers*. Intergovernmental Panel on Climate Change.

Manson, S., J. Shroeder, D. Van Riper, T. Kugler, and S. Ruggles. 2022. "IPUMS National Historical Geographic Information System: Version 17.0." `http://doi.org/10.18128/D050.V17.0`.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: a Ricardian Analysis." *The American Economic Review*, pp. 753–771.

Oehninger, E.B., C.Y.C.L. Lawell, and M.R. Springborn. 2017. "The effects of climate change on agricultural groundwater extraction." *Unpublished Working Paper*, pp. .

Pace, C., C. Balazs, K. Bangia, N. Depsky, A. Renteria, R. Morello-Frosch, and L.J. Cushing. 2022. "Inequities in Drinking Water Quality Among Domestic Well Communities and Community Water Systems, California, 2011–2019." *American Journal of Public Health* 112:88–97.

Pauloo, R.A., A. Escriva-Bou, H. Dahlke, A. Fencl, H. Guillon, and G.E. Fogg. 2020. "Domestic Well Vulnerability to Drought Duration and Unsustainable Groundwater Management in California's Central Valley." *Environmental Research Letters* 15:044010.

Perez-Quesada, G., N.P. Hendricks, and D.R. Steward. 2023. "The Economic Cost of Groundwater Depletion in the High Plains Aquifer." *Journal of the Association of Environmental and Resource Economists* 0:null.

Pfeiffer, L., and C.Y.C. Lin. 2012. “Groundwater Pumping and Spatial Externalities in Agriculture.” *Journal of Environmental Economics and Management* 64(1):16–30.

Provencher, B., and O. Burt. 1993. “The Externalities Associated with the Common Property Exploitation of Groundwater.” *Journal of Environmental Economics and Management* 24(2):139–158.

Rode, A., T. Carleton, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, A. Jina, R.E. Kopp, K.E. McCusker, et al. 2021. “Estimating a Social Cost of Carbon for Global Energy Consumption.” *Nature* 598:308–314.

Rosa, L., D.D. Chiarelli, M. Sangiorgio, A.A. Beltran-Peña, M.C. Rulli, P. D’Odorico, and I. Fung. 2020. “Potential for Sustainable Irrigation Expansion in a 3C Warmer Climate.” *Proceedings of the National Academy of Sciences* 117:29526–29534.

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2007. “Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California.” *Climatic Change* 81:19–38.

—. 2005. “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach.” *The American Economic Review* 95:395–406.

Schlenker, W., and M.J. Roberts. 2009. “Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change.” *Proceedings of the National Academy of Sciences* 106:15594–15598.

Schlenker, W., M.J. Roberts, and D.B. Lobell. 2013. “US Maize Adaptability.” *Nature Climate Change* 3:690–691.

Shapiro, J.S., and R. Walker. 2021. “Where Is Pollution Moving? Environmental Markets and Environmental Justice.” *AEA Papers and Proceedings* 111:410–14.

Sloat, L.L., S.J. Davis, J.S. Gerber, F.C. Moore, D.K. Ray, P.C. West, and N.D. Mueller. 2020. “Climate Adaptation by Crop Migration.” *Nature Communications* 11:1243.

Smith, S., and T. Beatty. 2023. “Extreme Temperatures and Field-Level Crop Quality, Yield, and Revenue.”, pp. 1–77. *Working Paper*. UC Davis. `https://sarahcsmith.github.io/assets/Tomato_Quality.pdf`.

Swain, D.L., B. Langenbrunner, J.D. Neelin, and A. Hall. 2018. "Increasing Precipitation Volatility in Twenty-First-Century California." *Nature Climate Change* 8:427–433.

Taraz, V. 2017. "Adaptation to Climate Change: Historical Evidence from the Indian Monsoon." *Environment and Development Economics* 22:517–545.

Taylor, C. 2023. "Irrigation and Climate Change: Long-run Adaptation and its Externalities." `https://drive.google.com/file/d/12dxZUpX052DsWIwfRZdtoyR-4QEOKW3O/edit`.

Wang, J., H. Yin, J. Anderson, E. Reyes, T. Smith, and F. Chung. 2018. "Mean and Extreme Climate Change Impacts on the State Water Project." A Report for: California's Fourth Climate Change Assessment.

Wooldridge, J.M. 2015. "Control Function Methods in Applied Econometrics." *The Journal of Human Resources* 50:420–445.

—. 2023. "Simple Approaches to Nonlinear Difference-in-Differences with Panel Data." *The Econometrics Journal* 26:C31–C66.

For Online Publication: Appendix

A.1 Dynamic Effects of Well Drilling

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

Dynamic Conceptual Model

Let the stock of wells in each period depend on the number of wells in the prior period plus the net change in wells between the last period and this period. We allow for the possibility that wells drilled today may be affected by both current and past weather. Bolded vector $\mathbf{s}_\tau$ denotes current and past surface water supplies at a time τ.

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

Now, denoted the current year of interest by t. Groundwater consumption in some future period T can be impacted by wells built in years prior to T because wells are persistent once built.

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

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

$$DTW_T(s_t,...,s_T) = DTW_t + \kappa \sum_{\tau=t}^{T} q_\tau(s_\tau)\Big(w_0 + \sum_{u=t}^{\tau} \Delta w_u(\mathbf{s_u})\Big) - \kappa \sum_{\tau=t}^{T} R_\tau(s_\tau)$$

$$= DTW_t + \kappa \underbrace{q_t(s_t)w_t(\mathbf{s_t})}_{\text{Contemporaneous consumption}} + \kappa \sum_{\tau=t+1}^{T} q_\tau(s_\tau)\Big(\underbrace{w_t(\mathbf{s_t})}_{\substack{\text{Future pumping from}\\ \text{stock of wells at } t}} + \underbrace{\sum_{u=t+1}^{\tau} \Delta w_u(\mathbf{s_u})}_{\substack{\text{Wells drilled in}\\ \text{years after } t}}\Big) - \kappa \sum_{\tau=t}^{T} R_\tau(s_\tau) \tag{A3}$$

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.

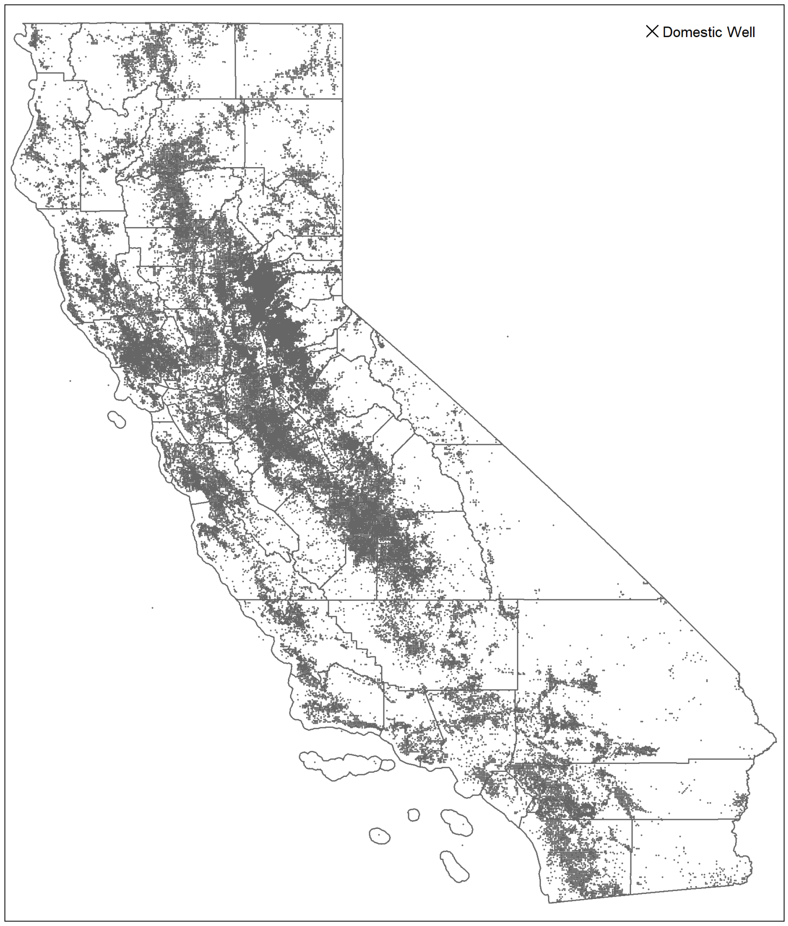
Then, assume a shock to surface water occurs in the contemporaneous time t. The effect on future groundwater levels can be decomposed as:

$$\underbrace{\frac{dDTW_T}{ds_t}}_{\text{cumulative effect}} = \kappa\Big[\underbrace{w_t(\mathbf{s_t}) \times \frac{dq_t(s_t)}{ds_t}}_{\substack{\text{contemporaneous}\\ \text{intensive margin}}} + \underbrace{q_t(s_t) \times \frac{\partial w_t(\mathbf{s_t})}{\partial s_t}}_{\substack{\text{contemporaneous}\\ \text{extensive margin}}} +$$

$$\underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_t(\mathbf{s_t})}{\partial s_t}}_{\substack{\text{future pumping}\\ \text{from wells drilled in } t}} + \underbrace{\sum_{\tau=t+1}^{T} q_\tau(s_\tau) \times \frac{\partial w_\tau(\mathbf{s_\tau})}{\partial s_t}}_{\substack{\text{future drilled wells}\\ \text{from } s_t}} - \underbrace{\sum_{\tau=t}^{T} \frac{\partial R_\tau(\mathbf{s_\tau})}{\partial s_t}}_{\text{recharge margin}}\Big]. \tag{A4}$$

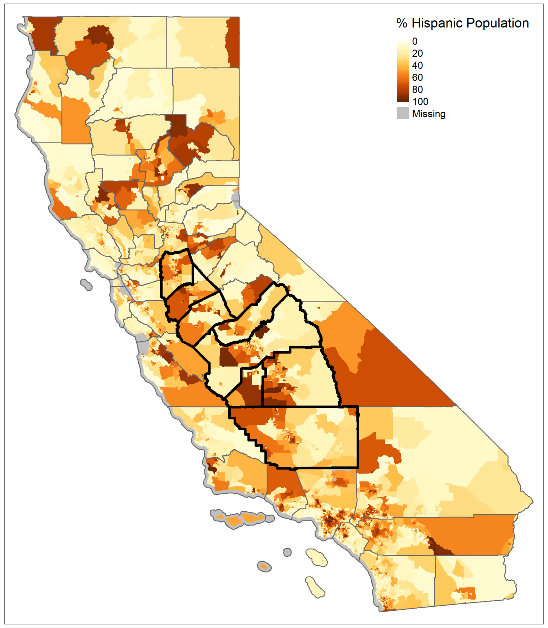
A.2 Supplementary Figures and Tables

Figure A1: Location of Domestic Wells



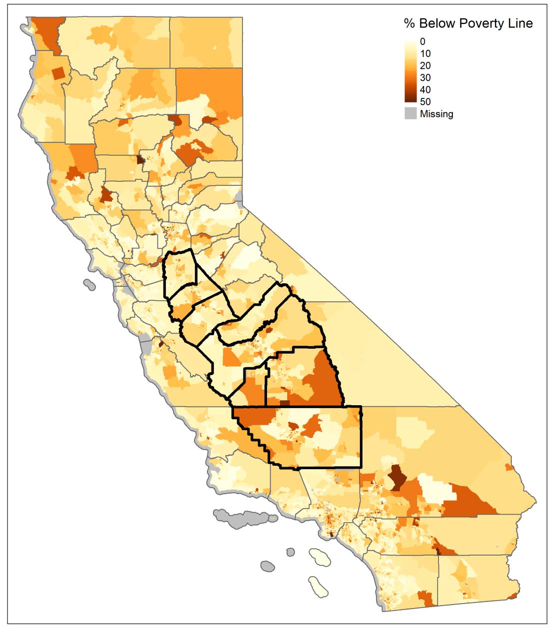
Note: Figure shows the location of domestic groundwater wells constructed. Data are from Well Completion Reports from DWR.

Figure A2: Population Demographics in California



% Hispanic Population

(a)

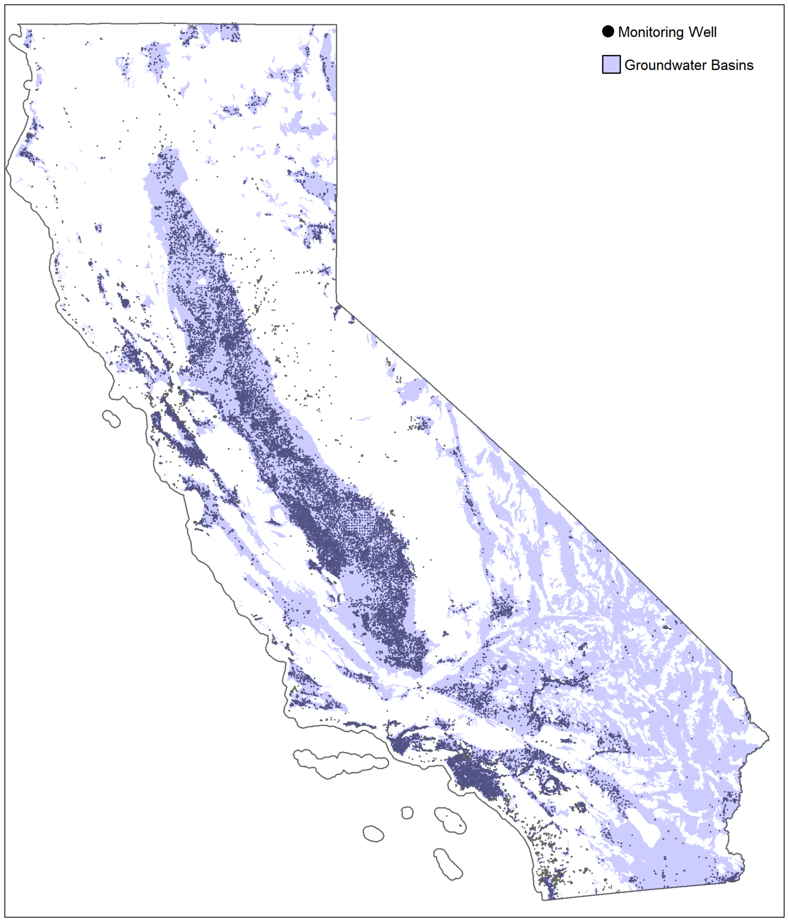


% Population below poverty line

(b)

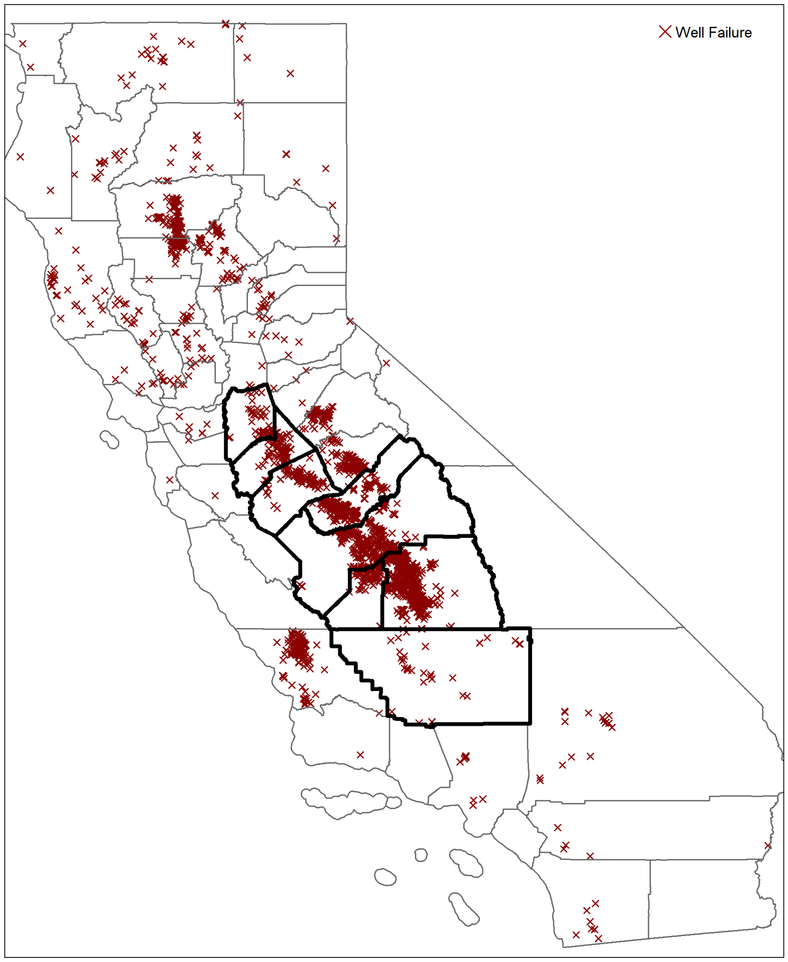
Note: Figure displays demographics at the Census tract level using data from 2020 (Manson et al., 2022). Panel (a) plots the percentage of the population that identifies as Hispanic. Panel (b) plots the percentage of households that fall below the federal poverty line for their household size. Bold county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

Figure A3: Location of Monitoring Wells in California Groundwater Basins



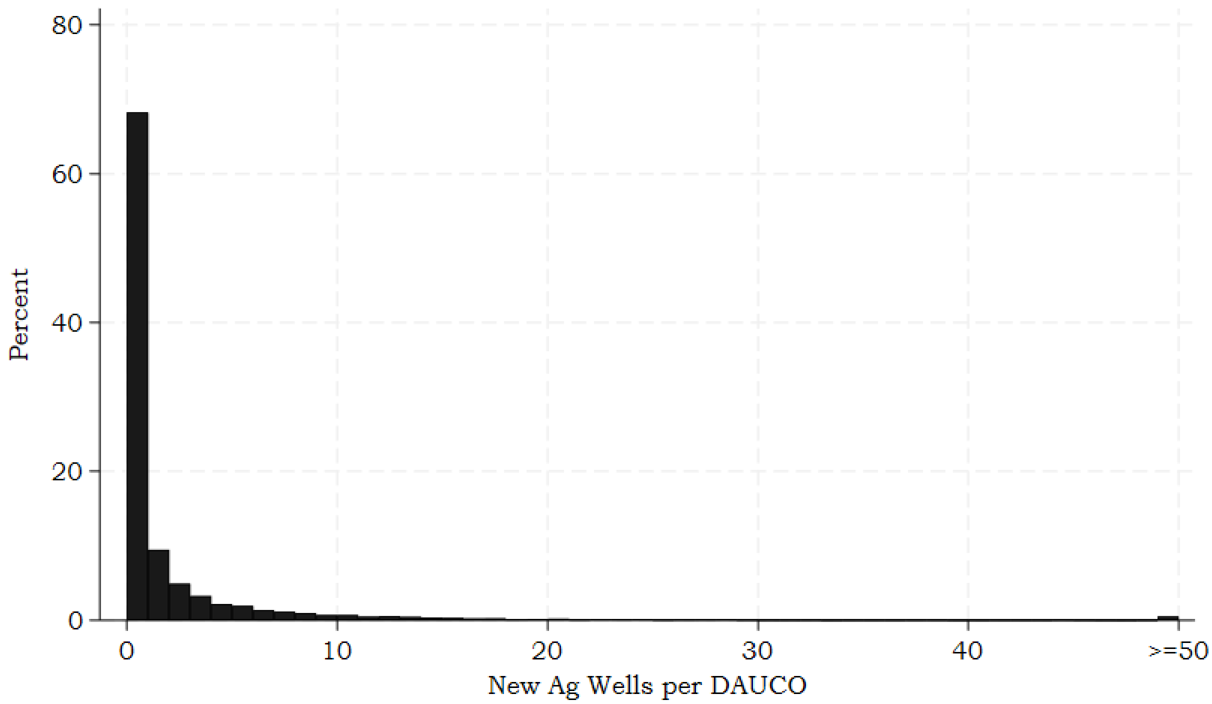
Note: Figure displays the locations of groundwater monitoring wells and California's principle groundwater basins. Each dot displays a unique groundwater monitoring well reported in our dataset. The blue shaded areas display the locations of Bulletin 118 groundwater basins in California.

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



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

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



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

Table A1: Agricultural SW Deliveries: First-Stage Results

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

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

Table A2: New Constructed Well Depth

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

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

Table A3: Destruction of Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation per crop acre (AF)	0.115	0.164	-0.0903	-0.00591
	(0.193)	(0.228)	(0.140)	(0.143)
Harmful Degree Days		-0.00215		-0.0228
		(0.00778)		(0.00814)
Observations	10,416	9,996	4,158	4,158
N Cluster	372	357	154	154
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

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

Table A4: Construction of New Agricultural Wells: Reduced-Form

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

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

Dynamic Empirical Estimation Results

Table A5 reports the dynamic effects up for up to 3 lag shocks on surface water deliveries and harmful degree days. The cumulative effects of this table are plotted in Figures 5 and A6.

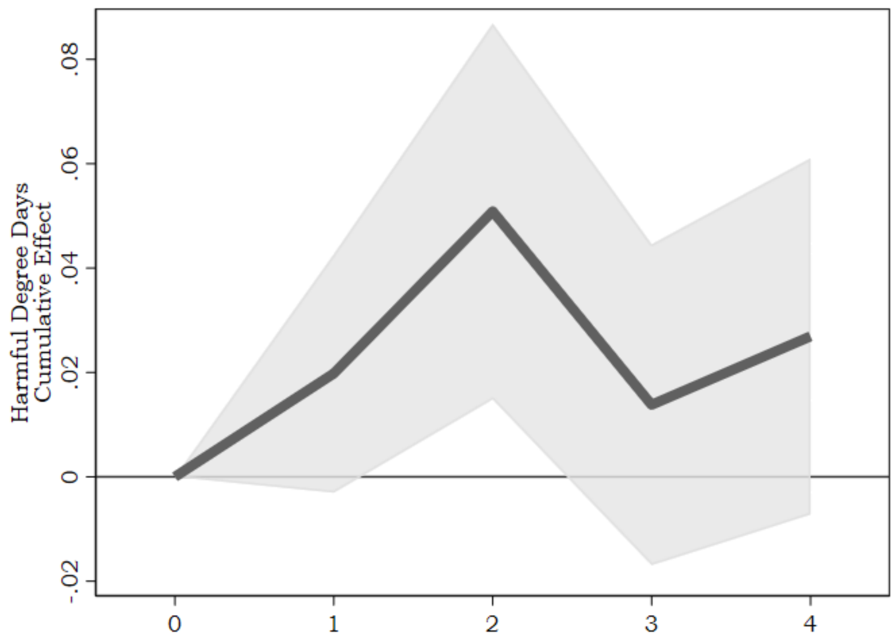
Table A6 considers the dynamics of agricultural well drilling. We report the results a linear IV for well construction, similar to columns (1) and (2) of Table 4 but now supplemented with up to three lagged years of agricultural surface water deliveries. Columns (2) through (4) each add an additional lag. In these specifications, deliveries are instrumented with surface water allocations.

Table A5: Lagged Changes in Groundwater Depth

	(1)	(2)	(3)	(4)
		ΔDTW		
Ag SW Deliveries (AF/ crop acre)	-2.914	-2.769	-2.828	-3.109
	(1.176)	(1.146)	(1.146)	(1.146)
L.Ag SW Deliveries (AF/ crop acre)		0.433	0.200	0.428
		(0.654)	(0.629)	(0.625)
L2.Ag SW Deliveries (AF/ crop acre)			-0.258	-0.406
			(0.699)	(0.724)
L3.Ag SW Deliveries (AF/ crop acre)				-0.637
				(0.418)
$\sum \beta_{deliveries}$	-2.914	-2.335	-2.887	-3.724
$p_{deliveries}$	0.0138	0.00812	0.00446	0.0000336
Harmful Degree Days	0.0309	0.0226	0.0245	0.0198
	(0.0115)	(0.0126)	(0.0130)	(0.0117)
L.Harmful Degree Days		0.0168	0.0307	0.0311
		(0.0100)	(0.0118)	(0.0126)
L2.Harmful Degree Days			-0.0207	-0.0371
			(0.00978)	(0.0130)
L3.Harmful Degree Days				0.0131
				(0.0109)
$\sum \beta_{hdd}$	0.0309	0.0394	0.0345	0.0269
p_{hdd}	0.00795	0.00455	0.0340	0.123
Observations	560,931	555,846	550,874	545,710
N Cluster	282	281	281	280
Weights	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$	$\frac{\text{Crop Acres}}{\text{\# wells}}$
Other Weather	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses. $p_{deliveries}$ and p_{hdd} report the p-values for a t-test of whether the sum of the respective coefficients is different from zero.

Figure A6: Cumulative Impulse Response of Harmful Degree Days on ΔDTW



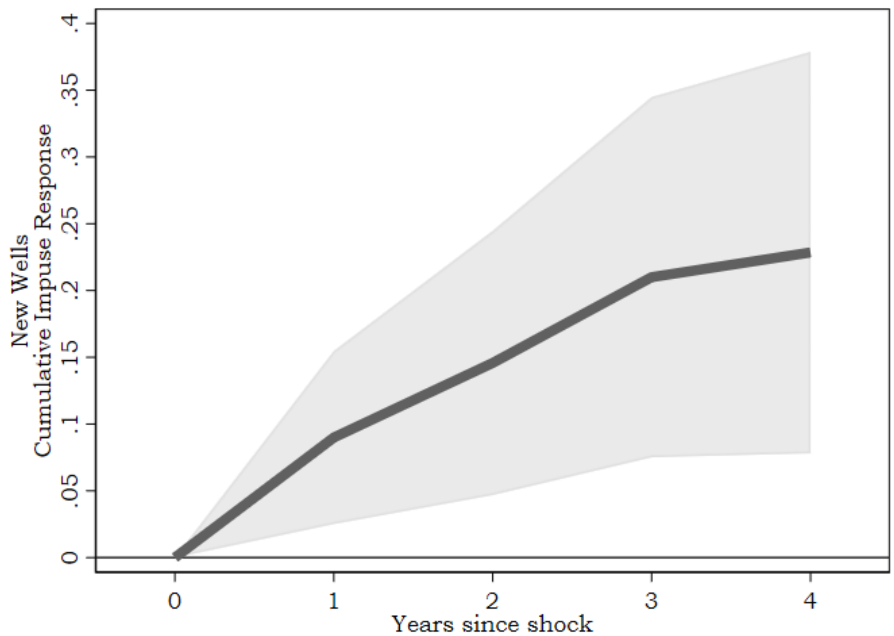
Note: Figure displays the cumulative impulse response of a single harmful degree day in the initial year. Dependent variable is ΔDTW and the dark line reflects the sum of contemporaneous and lagged coefficients on harmful degree days for each year since the initial shock. Light shading reflects confidence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

Table A6: Lagged Agricultural Well Construction

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

Note: Table reports regression results from a lagged linear IV model. The dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses. $p_{deliveries}$ and p_{hdd} report the p-values for a t-test of whether the sum of the respective coefficients is different from zero.

Figure A7: 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.

Table A7: 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 5 and table A5
κ	8.33	unitless	Inverse storativity or specific yield Department of Water Resources (2020)
$\sum_{\tau=t}^{T} \frac{\partial R_\tau(\mathbf{s}_\tau)}{\partial s_t}$	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 (8). California Water Balance Data used to calculate recharge coefficient can be accessed at `https://data.cnra.ca.gov/dataset/water-plan-water-balance-data`

Additional Empirical Specifications

We conduct two falsification tests of our primary model. First, Table A8 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 A9. These results indicate that municipal and industrial water supplies are actually positively correlated with agricultural well construction, which is opposite of the effect of agricultural surface water. None of these coefficients are significant, and again, supports that the results in Tables 4 and A4 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

Table A8: Construction of New Domestic Wells

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

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

Table A9: Construction of New Agricultural Wells: Municipal and Industrial Surface Water

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

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