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

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Abstract

Adaptation to climate and weather shocks can be costly for producers, but it also may impose negative externalities on vulnerable populations. We study this in the context of groundwater in California and evaluate the effects of annual fluctuations in weather and surface water supplies on agricultural well construction and access to drinking water. Using the population of geocoded wells, we show that farmers respond to extreme heat and surface water scarcity through new well construction. This mitigating behavior by agricultural users imposes costs: Extreme heat and surface water scarcity also lower local groundwater levels and cause domestic well failures. While groundwater extraction helps producers reduce the damage from environmental shocks, it also harms access to drinking water supplies in marginalized communities.

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1 Introduction

The costs of climate change are expected to be broad in reach and disproportionately borne by the poor (Hsiang, Oliva, and Walker, 2019). The latter occurs in part because the magnitude of damages depends on the ability to adapt, and poorer households are less likely to have the means to respond (Dell, Jones, and Olken, 2012, 2014; Burke and Emerick, 2016; Jessoe, Manning, and Taylor, 2018; Rode et al., 2021). Averting actions taken by some to mitigate climate damages may also impose externalities that are disproportionately realized. However, little is known about the extent to which avoidance behaviors taken to reduce climate damages impose costs on others.

We study this in the context of groundwater in California by evaluating the extent to which mitigating behaviors taken in response to heat and surface water scarcity lead to groundwater depletion and drinking water well failures. Historically, the agricultural costs of heat and drought in California have been moderate, partly because precipitation is an inaccurate measure of total water availability for irrigated agriculture (Schlenker, Hanemann, and Fisher, 2005, 2007; Edwards and Smith, 2018). In California, farmers instead rely on surface water supplies conveyed via canals and water projects and groundwater pumped from wells. This latter resource has operated as a critical mitigation strategy to dampen the agricultural costs of surface water reductions and heat, and may explain why some forecast that the costs of climate change in California will be minimal (Mendelsohn, Nordhaus, and Shaw, 1994; Lund et al., 2018).[1] However, this groundwater extraction also imposes costs on current users and future users. A declining water table may impose a pumping externality which makes groundwater irrigation costlier for neighboring farms and a stock externality which makes it unavailable to farmers in the future (Provencher and Burt, 1993; Roseta-Palma, 2002; Brozović, Sunding, and Zilberman, 2010; Pfeiffer and Lin, 2012; Edwards,

[1] Climate change is expected to increase the frequency and severity of extreme heat and drought, make precipitation more variable, and reduce soil moisture (Swain et al., 2018). Collectively, these factors will increase agricultural demand for water and introduce large uncertainty into surface water availability for agricultural irrigation. To buffer against surface water curtailments and increased demand, agricultural users have often drawn from non-renewable groundwater reserves.

2016; Merrill and Guilfoos, 2017).

Less well understood is the acute and contemporaneous costs that groundwater pumping may exact on drinking water supplies in surrounding communities. Many households rely on private domestic wells for drinking water purposes. These users are concentrated in California's San Joaquin Valley, and are disproportionately low income and people of color.[2] Access to drinking water supplies among disadvantaged communities is a growing concern, with recent forecasts projecting that 10,500 domestic wells in the San Joaquin Valley are expected to run dry by 2040 (Pauloo et al., 2020).

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

To empirically measure these impacts, we constructed a panel spanning 30 years on drinking and groundwater access for all agricultural water districts in California. We combined the universe of groundwater wells constructed, data on domestic well failures, groundwater depth data from groundwater monitoring stations, gridded weather data, and annual data on district-level sur-

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

face water supplies. Information on groundwater well construction and well failures includes the location and date of construction, well depth, and well type for over a million wells. Schlenker and Roberts (2009) provide measures of temperature and precipitation derived from PRISM monthly data and daily weather station observations, and data from Hagerty (2021) measures the universe of surface water allocations in California by area and year from 1993 to 2020. These detailed data allow us to deploy an instrumental variables panel data approach that exploits annual fluctuations in temperature and surface water shocks, and control for a number of factors, such as fixed differences, and annual shocks, such as recessions, that likely impact water access and agricultural producer's decision making in these local areas.

A first set of results indicates that extreme heat and reductions in agricultural surface water supplies lower the depth to the groundwater table. A one acre-foot (AF) reduction in the agricultural surface water allocation to every California cropland acre lowers local groundwater levels by an additional 4 feet. An additional harmful degree day reduces groundwater levels by 0.5 inches. Declining water tables suggest that the costs of climate change may be larger in the long-run if farmers cannot buffer with groundwater resources (Hornbeck and Keskin, 2014; Auffhammer, 2018).

A second central result indicates that farmers are responding to heat and surface water scarcity through the construction of groundwater wells. We estimate that for each acre foot (AF) of reduced surface water allocations for agriculture, the annual rate of agricultural well construction increases by 46%. Using an approximated cost of $75,000 to construct an agricultural well (CVFPB, 2020), this translates to a back-of-the-envelope $37 million dollars invested annually in extensive-margin adaptation behavior by California farmers. This number also provides a lower-bound estimate on the avoided climate damages to California agriculture.

Our finding that extreme heat will increase groundwater demand brings a new data point to our understanding of how climate change will influence water resources. While climate projections indicate increased year-to-year variation in rainfall, projections on the amount of precipitation are less clear (Jessoe, Mérel, and Ortiz-Bobea, 2018). Our results highlight that even if water supplies remain unchanged, warmer temperatures will increase demand for groundwater, with an additional harmful degree day increasing well construction by 1.2%. They also offer empirical evidence of historical agricultural adaptation to heat, with groundwater extraction serving as a critical buffer to mitigate the costs of extreme heat in California (Burke and Emerick, 2016; Hornbeck and Keskin, 2014; Barreca et al., 2016; Auffhammer and Schlenker, 2014).

Extreme heat and surface water scarcity also lead to domestic well failures, with a 1 AF decrease in surface water supplies and an extra HDD increasing failures by 5 and 0.2 percentage points, respectively. These results are consistent with a theoretical framework and computational hydrology model in which increased groundwater consumption among agricultural users comes at the cost of drinking water supplies through the channel of a declining water table (Pauloo et al., 2020). More broadly, our work adds a new dimension to our understanding about inequities in exposure to environmental costs (Banzhaf, Ma, and Timmins, 2019). A recent literature documents the unequal rate at which disadvantaged communities are exposed to pollution and the relative health costs, as well as the distributional implications of environmental regulations intended to reduce exposure (Currie, 2011; Hernandez-Cortes and Meng, 2020; Bento, Freedman, and Lang, 2015). Our work implies that inequities arise from the absence of regulation, specifically that mitigating behaviors by those with access to capital will impose costs on disadvantaged groups. When implementing proactive policy aimed at easing the burden of climate change, policymakers must ensure they are not unintentionally burdening the most vulnerable individuals.

This finding is also informative for the design of drinking water regulations in the United States. Drinking water quality issues impose severe costs in less advantaged communities, and are a growing concern in rural communities in the Southwest (Allaire, Wu, and Lall, 2018; Christensen, Keiser, and Lade, 2021; Marcus, 2021). Drinking water is also becoming increasingly expensive, making affordability a growing concern (Cardoso and Wichman, 2022). We find that access to drinking water supplies as measured by domestic well failures and depth to the water table will be exacerbated under climate change, and disproportionately affect disadvantaged communities.

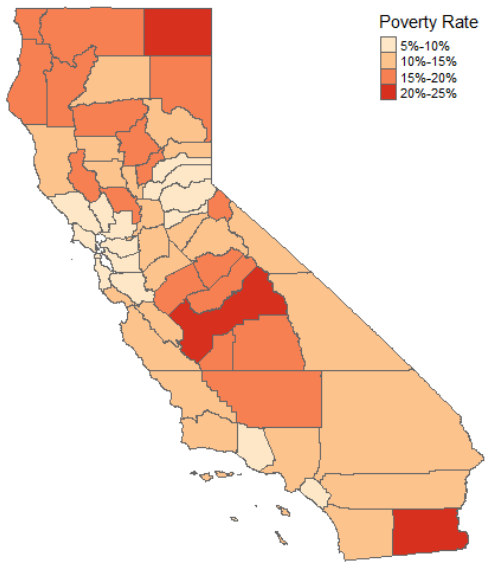
2 Agriculture and Rural Communities in California

California agriculture plays a significant role in the global food value chain. The agricultural industry in California employs over 400,000 people and generates over $50 billion in agricultural sales, the most of any state in the United States. California also contributes the entire U.S. supply of some fruits and nuts, like almonds and grapes (CDFA, 2020).

California's Central Valley and other productive agricultural land in the Western U.S. receives insufficient rainfall for agricultural production. Irrigation infrastructure and technology has played a significant role in the development of the agricultural economy in these states (Hornbeck and Keskin, 2014; Edwards and Smith, 2018). In contrast, agriculture east of the 98th meridian primarily relies on periodic rainfall for crop production. Agricultural irrigation in California consumes over 80% the state's water and occurs via surface water and groundwater, with the latter accounting for roughly 40% of water supplies (Hrozencik and Aillery, 2022).

Agricultural production in California is heavily concentrated in the San Joaquin Valley (SJV) in central California. The counties that comprise the SJV are largely rural and experience some of the highest poverty rates in the country as shown in figure 1. (A secondary center of agriculture is the Imperial Valley, which appears on the map as the high-poverty county in the southeastern corner of the state.) Many households in rural areas utilize private domestic wells and depend on groundwater wells for residential use and drinking water supply. The geographic intersection of agricultural groundwater use and groundwater-dependent households makes these areas particularly vulnerable to climate change damages.

Figure 1: Poverty Rate of California Counties



Note: The figure graphs the percent of the population in poverty by California county. Data come from USDA Economic Research Service.

2.1 Surface Water Irrigation

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

Surface water is allocated through a complex first-in-time, first-in-right scheme that has persisted since the early 1900s. A water user or entity will either hold a right to divert water directly from a nearby river or possess a long-term contract to water deliveries through canals operated by the State Water Project or the federal Central Valley Project. Most water rights and contracts are held by irrigation districts – local government agencies – which then supply water to farms within their jurisdiction. Water is typically rationed by quantity rather than price, and by custom or law supplied equally to producers on a per-acre basis.

Rights and contracts do not guarantee water supplies in any given year. Water rights are satisfied in order of seniority, though enforcement is largely informal. In practice most agricultural water rights are senior to the federal and state water projects, which bear the brunt of water shortages in dry years. Contracts with the federal and state water projects constitute a maximum annual volume and a contract category. Each year, the U.S. Bureau of Reclamation and the California Department of Water Resources (DWR) announce a set of allocation percentages, which determine how much of their maximum volume contractors in each category will receive. In recent years, it is common for allocation percentages to be set as low as 0% during droughts. Thus, the impacts of drought manifest through changes in surface water.

Year-to-year fluctuations in surface water allocations are determined by the government agencies through bureaucratic processes that depend on reservoir levels, environmental conditions, and weather forecasts. Allocations are announced prior to the growing season, before producers make input decisions. Actual surface water deliveries can differ from allocations in a few ways. Irrigation districts can purchase additional water mid-season on the spot market, pump water from groundwater banks, or reserve water for up to a year in response to environmental conditions. Hence, actual surface water deliveries are potentially endogenous to drought. To control for potential endogeneity in surface water supplies, we instrument deliveries with allocation, similar to Hagerty (2021). We discuss this in further detail in the empirical framework.

2.2 Groundwater Irrigation

Groundwater has traditionally acted as a buffer to fluctuations in surface water supply. Groundwater accounts for 80% of water supplies during times of drought. Changes in surface water deliveries are thus correlated with groundwater pumping which affects the water table. Historically, this sector has been largely unregulated. Owners of land have the right to drill wells and pump groundwater with few restrictions. The open-access nature of groundwater has led to declining groundwater levels, higher costs to pump, and other negative consequences. As a result, a historic groundwater regulation was passed in 2014 – the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater in California by 2042.[3]

The cost of groundwater well construction varies widely based on the completed drilled depth and intended use. Residential domestic wells are typically between 100 and 300 ft deep and cost approximately $10,000. Agricultural wells are drilled between 300 and 500 ft deep on average and cost between $50,000 and $100,000. They are drilled with a wider diameter than residential wells to allow for higher flow rates. New wells are required to be reported to the DWR and are typically constructed in under a week (CVFPB, 2020).

2.3 Drinking Water in Rural Communities

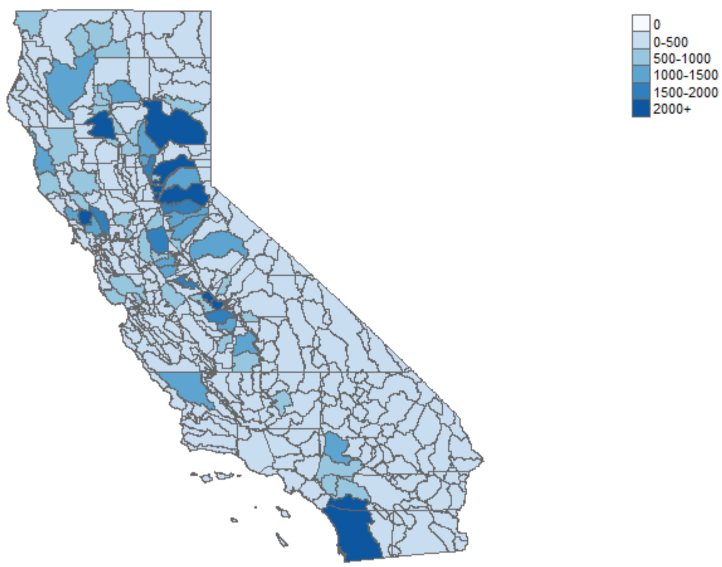
Most individuals in California receive residential and drinking water from community water systems regulated by the Safe Drinking Water Act (SDWA)[4]. However, many individuals outside of community water system boundaries, like households in rural areas, rely on private groundwater wells for their domestic water supply. Figure 2 shows the number of domestic groundwater wells constructed from 1993 to 2020 across the state. Deteriorating drinking water quality is pervasive for many of these users, especially since these water sources are outside the jurisdiction of the SDWA. Declining groundwater tables also threaten safe and affordable access to residential water for this subset of the population.

Counties in California's San Joaquin Valley experience some of the highest poverty rates in the country and are a large percent Latino/a (Huang and London, 2012). Many of these individuals are also employed by the local agriculture industry (Martin and Taylor, 1998). Table 1 reports the proportion of reported well failures as a fraction of the total number of domestic wells by local

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

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

Figure 2: Total Domestic Wells Constructed from 1993-2020



Note: The figure shows a count of the number of domestic groundwater wells constructed from 1993 to 2020 by Detailed Analysis Unit by County, the smallest water management planning unit defined by the California DWR. Data are from DWR.

demographics, agricultural intensity, and well characteristics. Wells in census tracts with above median poverty rates and above median percent non-white populations report well failures at a higher rate than populations below the median. Additionally, areas where land is cultivated at a higher percent for agricultural use also experience well failures at a higher rate.

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

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

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

3 Conceptual Model

We develop a conceptual model of changes in the depth to the groundwater table as a function of properties of the aquifer and groundwater demand from agricultural pumpers. We decompose the net effect by changes in new wells constructed (extensive margin) and changes in the intensity of pumping at each well (intensive margin) in the style of Hendricks and Peterson (2012). We model agricultural groundwater use as a function of surface water availability, s, and a measure of extreme heat, h. In the context of California, approximately 60% of agricultural irrigation is supplied from surface water. Additionally, warmer growing seasons will likely impact irrigation for crop acres (Rosa et al., 2020). Let $w(s,h)$ then be the number of wells used for agricultural irrigation. Similarly, let $q(s,h)$ determine the average amount of groundwater application per well. Together, the total volume of groundwater use, which determines the height of the groundwater table, is equal to $w(s,h) \times q(s,h)$. To translate volume of water extracted to changes in water table depth, we multiply this by a constant hydrologic aquifer storage coefficient, κ, to translate volume of water extracted to a unit decline in the water table.[5]

Depth to the water table, DTW, is therefore given by:

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

Differentiating with respect to either surface water or heat yields:

$$DTW'(s,h) = \kappa \big[w'(s,h) \times q(s,h) + q'(s,h) \times w(s,h) \big] \tag{2}$$

where $w'(s,h)$ reflects changes in the number of groundwater irrigation wells used due to surface water or heat shocks – the extensive-margin response. Likewise, $q'(s,h)$ reflects the intensive-margin change, or the change in the average volume of groundwater pumped per-well due to changes in surface water or heat. In our empirical analysis we are able to estimate both the gross change in groundwater levels by climate-induced changes in groundwater demand and the extensive-margin effect of farmers adapting to surface water scarcity and heat through new well construction.

Groundwater extraction to buffer against the costs of heat and surface water scarcity may impose external damages on others by increasing the scarcity of groundwater supplies through a lowering of the water table. We assume that these damages are proportional changes to the groundwater level. That is, the external damages, D, are increasing linearly in the decline of the depth to the groundwater. Equation 3 outlines this relationship, where c is the marginal external

[5] κ is defined as the inverse of hydrologic storativity of an aquifer. Storativity measures the volume of water pumped from the aquifer per foot decline in groundwater table, per acre of the aquifer.

damage associated with a foot reduction in the water table.

$$D(s,h) = c \times DTW'(s,h) \tag{3}$$

In our empirical setting, we shed light on the magnitude of these externalities by showing the extent to which changes in surface water scarcity and heat lead to household well failures.

4 Data

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

Unit of Observation

Due to the nature of the data, it is necessary to define a geographic unit of aggregation for several variables. When necessary, we aggregate to the Detailed Analysis Unit by County (DAU by Co or DAUCO) boundaries. DAUs divide California's hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis by California Department of Water Resources. Historically, DAUs followed the United States Geological Service's watershed boundaries (HUC-8). As additional water infrastructure was added to California, DAU boundaries were updated to account for water district boundaries so that water accounting could be completed more accurately. At present, DAUs are a combination of watershed and water district boundaries, which often overlap counties. In these cases, we further disaggregate the unit into DAU by County – the smallest geographic unit of aggregation used by DWR. We use these boundaries to define the count of new agricultural wells annually and the agricultural surface water delivered. Because DAUCOs are definitions of convenience without any special economic significance, we weight our regressions by crop area so that our estimates are representative for the average acre of cropland in California.

Table 2: Summary Statistics

	Unit	Count	Mean	SD	Min	Max
Outcomes:						
New Ag Wells	DAUCO	10,416	11.116	19.428	0	316
Depth to Groundwater (ft)	Monitoring Well	575,410	62.882	80.419	0	2714.08
ΔDTW	Monitoring Well	575399	0.299	6.068	-58.7	56.3
Probability of Domestic Well Failures	Domestic Well	473,940	0.025	0.157	0	1
Independent Variables:						
Ag SW Allocation (AF/crop acre)	DAUCO	9,660	2.333	2.043	0	10
Ag SW Deliveries (AF/crop acre)	DAUCO	10,416	2.233	1.914	0	10
Harmful Degree Days	DAUCO	9,996	97.235	86.881	0	622.3141
Growing Degree Days	DAUCO	9,996	3,535.366	659.927	632.4846	5813.042
Annual Precipitation (mm)	DAUCO	9,996	350.267	233.430	11.40778	4668.895
Crop Acres	DAUCO	10,416	169,741.485	131332.890	.2222608	502692.3

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

Depth to the Water Table

We use groundwater monitoring wells from groundwater basins across the state to measure depth to the groundwater table (DTW). We compile these measures from two sources: 1) The State Water Resources Control Board (SWRCB) Groundwater Information System and 2) DWR's Periodic Groundwater Level data. We append these two datasets and select a single annual measurement for each monitoring well prior to the start of the following year's growing season. For example, we assign the final groundwater depth of 2015 as the observed groundwater depth nearest to March 15, 2016. This ensures that we realize the cumulative effects of groundwater pumping and recharge throughout the current year and prior to the water intensive months of next year. We take the first difference of DTW as our final outcome variable to estimate the year-to-year changes in the groundwater table as a result of surface water scarcity.

To remove outlier observations of DTW, we exclude observations that are more than 1.5 times the inner decile range of all other changes in groundwater levels reported from monitoring wells in the DAUCO over our sample. This rule removes observations that observe drastically different changes in groundwater levels than other local groundwater measures.[6] We study the outcome of changes in DTW at the monitoring well level, where all monitoring wells in a DAUCO are assigned the same volume of surface water allocation and delivery in a given year. Therefore, we cluster our standard errors at the DAUCO level.

Well Construction

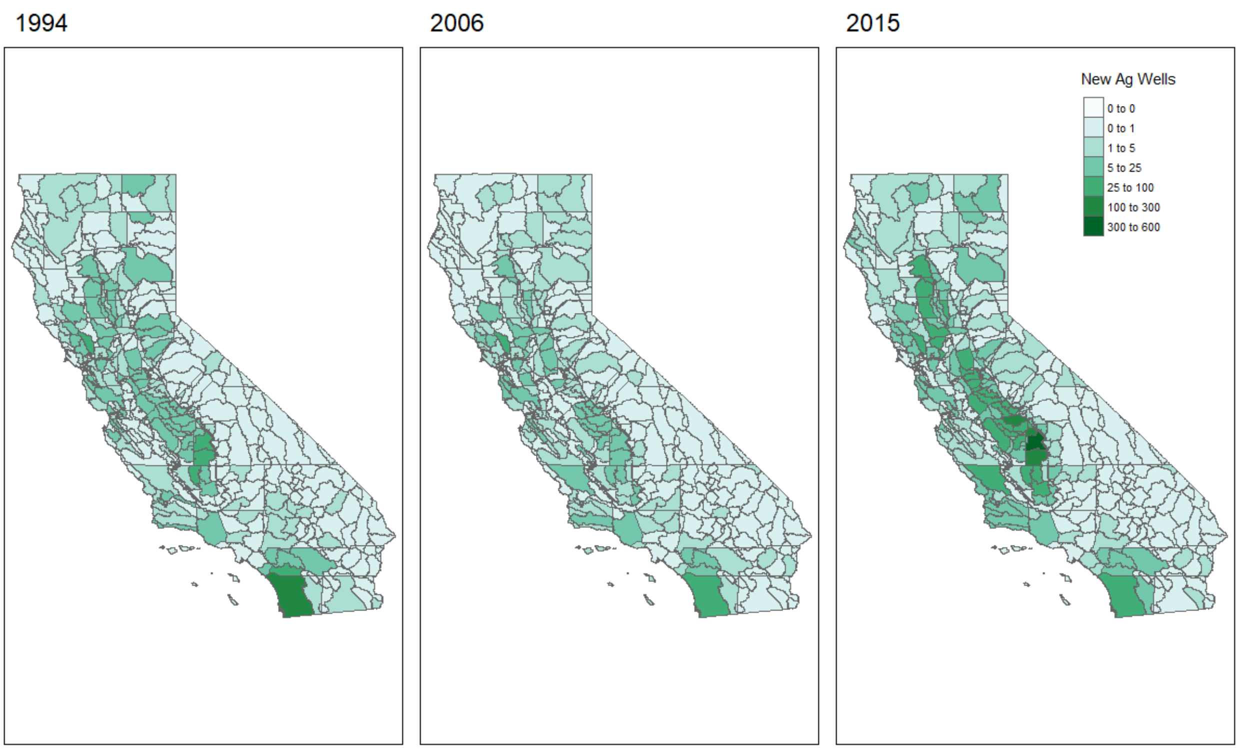
One outcome variable of interest measures the extensive-margin adaptation to surface water scarcity and extreme heat through the metric of new agricultural well construction. We use the universe of Well Completion Reports from DWR, which reports each well's location, the drilled depth of the well, intended use, and other characteristics. To measure adaptive response, we count the total number of new agricultural irrigation wells per DAUCO per year. Figure 3 maps new agricultural well construction for the years 1994, 2006, and 2015. The Central Valley of California experiences the most severe shocks to agricultural surface water curtailment, and these areas appear to respond the most in scarce water years by constructing new agricultural wells.

Well Failures

Beginning in 2014, DWR created a system for households to report domestic well failures. These data are now publicly available and regularly updated. These data contain the coordinates for the reported dry well, the date the issue started, and if the issue was resolved. We create a panel of all domestic wells in California from the Well Completion Reports. We geographically match the reported failures to the domestic wells from the Well Completion Reports. The final dataset for the analysis on well failures spans from 2014-2021, where *failure=1* for a domestic well in a given year if it is reported in the well failure database. For all other years, we assume *failure=0*. Hence,

[6] Some of these outlier observations are the result of a misplaced decimal, while other errors could occur from monitor errors. We cannot easily identify the source of measurement error in these data in order to assign accurate values, and therefore, remove these observations to reduce measurement error in our coefficient estimates.

Figure 3: New Agricultural Well Construction



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

our primary analysis of the externality created from agricultural adaptation is the linear probability of domestic well failure as a function of surface water and extreme heat. While this may be an undercount of the true number of domestic well failures, since household reporting is voluntary, it is an improvement on past approaches that have had to estimate if a well has gone dry based on assumptions about the relationship between well depth and groundwater table height.

Surface Water Allocations and Deliveries

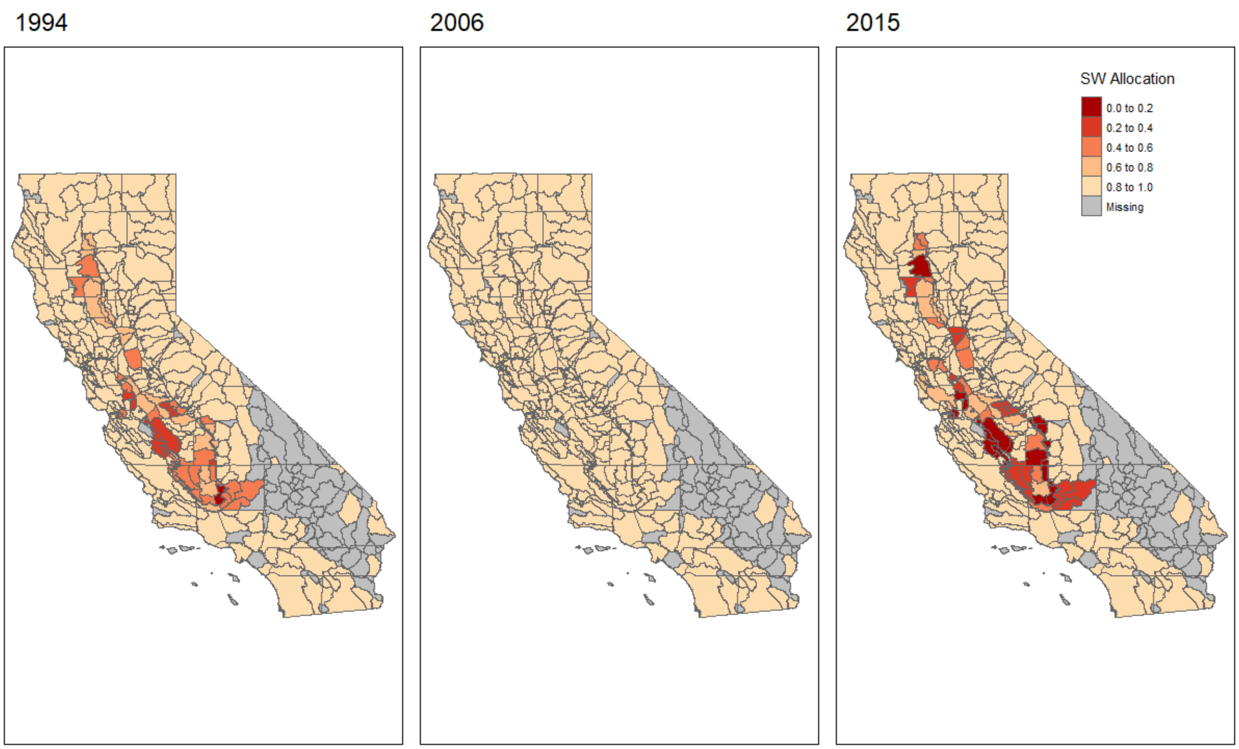
As measures of water scarcity, we use spatial and temporal variation in agricultural surface water allocations and deliveries throughout California from Hagerty (2021). These annual data provide volumes of water allocations and water deliveries from the Central Valley Project (CVP), State Water Project (SWP), the Lower Colorado Project, and surface water rights from 1993-2020.[7] We spatially aggregate these volumes to the DAUCO level. Because the place of use may differ from the point of delivery, this variable is subject to a greater degree of measurement error as the geographic unit of analysis becomes smaller. We transform total water allocations and deliveries by dividing by cropland acres in each DAUCO. Our final measure of surface water supplies captures the volume of surface water delivered in acre feet (AF) per cropland acre in the DAUCO. Because there are a number of extreme values, likely due to measurement error, we Winsorize this variable at 10 AF per acre. Figure 4 displays the variation across DAUCO areas within a given year and the locations most impacted by curtailments in drought years, 1994 and 2015. In the wet year of 2006, we see that all areas received high allocation percentages.

Weather

We measure extreme heat and precipitation using weather observations from Schlenker and Roberts (2009) and PRISM climate data. We measure extreme heat through "harmful degree days" (degree

[7] All months of 2021 were not yet reported at the time analysis was performed. The partial-year data for 2021 is included in the dataset, but we exclude 2021 in the estimation. Including partial 2021 data does not change point estimates, but standard errors do increase because of this discrepancy.

Figure 4: Agricultural Surface Water Allocation Percentages



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

days over 32 degrees Celsius) and "growing degree days" (degree days over 8 and below 32 degrees Celsius). We also control for local annual precipitation reported in millimeters. Schlenker and Roberts (2009) data, which are derived from PRISM weather station observations, ends in 2019. Therefore, we supplement weather observations from the raw PRISM data for 2020 and 2021.

5 Empirical Model

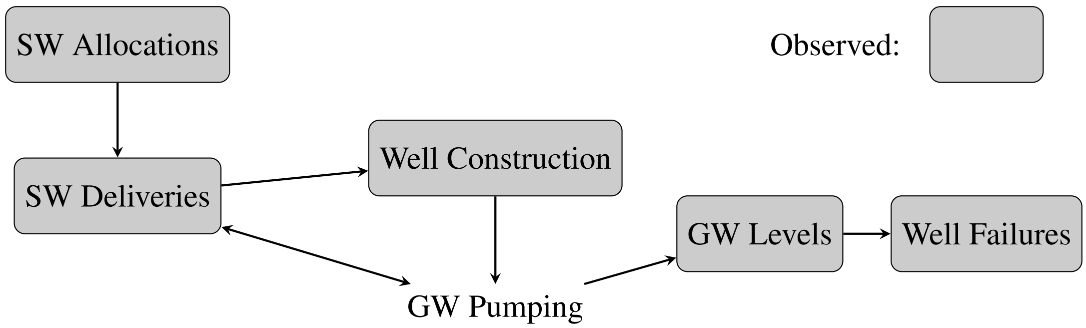
California presents a rich context to study climate change adaptation strategies and their subsequent external costs. Our empirical framework uses annual fluctuations in weather, surface water supplies, agricultural well construction, depth to the groundwater, and domestic well failures from 1993-2020 to measure three reduced-form effects. First, we attempt to causally identify the effects of extreme heat and surface water scarcity on year-to-year changes in the depth to the groundwater table. The lowering of groundwater levels leads to well failures of shallow household drinking water wells, the main external cost of concern. We next estimate the reduced-form effect of surface water scarcity and heat on domestic well-failure.

Changes in water table depth in response to heat and surface water scarcity are likely driven by additional groundwater pumping, via both new well construction (extensive margin) and through increased intensity at existing wells (intensive margin). Since groundwater pumping is unobserved, we estimate the effect of drought on new agricultural well construction, an observable measure of adaptation behavior by California farmers.

5.1 Causal Empirical Chain

Figure 5 illustrates the empirical link between observable and unobservable variables in our context. A chain for extreme heat and its impacts on groundwater outcomes is analgous by replacing

Figure 5: Causal Empirical Chain



Note: The figure charts a conceptual framework for the empirical relationships from water scarcity to domestic well failures. Groundwater pumping is unobserved.

surface water allocations and deliveries by observed harmful degree days.[8] Because groundwater pumping is likely correlated with new well construction, surface water deliveries, and groundwater levels, yet is unobserved, we are limited to the identification of the three reduced-form effects just mentioned. We cannot credibly estimate the effect of agricultural well construction on well failures because the potential instrument for well construction – allocations – would violate the exclusion restriction through its correlation with unobservable pumping.

5.2 Estimation and Identification

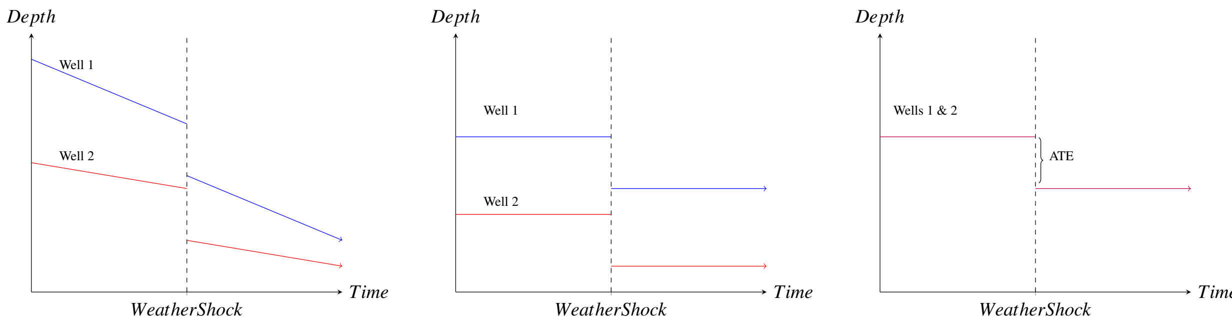
Outcome 1: Changes in Depth to the Water Table

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

$$\Delta DTW_{it} = \beta_1 SWD_{it} + \beta_2 HDD_{it} + B' X_{it} + \lambda_t + \alpha_i + \varepsilon_{it}. \tag{4}$$

[8] Extreme heat is unlikely to be endogenous to groundwater pumping in the same way as surface water deliveries since deliveries can be adjusted conditional on the amount of groundwater pumped. Therefore, we expect extreme heat to impact groundwater pumping, while the reverse is not true, which would be depicted by an arrow moving in a single direction from extreme heat to groundwater pumping in the analogous figure.

Figure 6: Difference-in-Differential Trends Framework



Groundwater (DTW) (a) ΔDTW (b) ΔDTW + FE (c)

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

The dependent variable, ΔDTW_{it} is the year-to-year change in the depth to the water table for well i in year t. Annual observations of the depth to the water table (DTW) measure the stock of groundwater availability, which represent the cumulative outcome of annual groundwater pumping and recharge. We instead take the first difference of depth to the groundwater, ΔDTW_{it}, so that our outcome measures the annual flow to the underlying stock. Our coefficients of interest, β_1 and β_2, measure the annual marginal change in ΔDTW for a unit change in surface water and harmful degrees days, respectively. Fixed effects α_i absorb well-level differential trends over time, allowing for each well to have different linear temporal trends all else equal, as illustrated in Figure 6. Year fixed effects are captured by γ_t and control for aggregate annual shocks like changes in statewide policies. The vector X_{it} captures other localized weather shocks, including precipitation and growing degree days. Our motivation for conditioning on other weather shocks is that precipitation may be correlated with surface water deliveries or heat and groundwater extraction and thus changes in the depth to the water table.

Of concern is the potential endogeneity between drought and surface water deliveries. In low surface water years, irrigation districts can influence their total delivery amount by purchasing water on the spot market or drawing from water banks. We exploit California's water allocation system, where allocations are set ahead of the season based on plausibly exogenous environmental conditions, as an instrument for surface water deliveries in a two-stage instrumental variables approach, following Hagerty (2021):

$$\begin{aligned} \Delta DTW_{it} &= \beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + B'X_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \\ SWD_{it} &= \gamma_1 SDA_{it} + \gamma_2 HDD_{it} + \Gamma' X_{it} + \lambda_t + \alpha_i + \mu_{it}. \end{aligned} \tag{5}$$

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

Identification of the effect of surface water scarcity hinges on two assumptions related to the instrument. The first is that allocations affect changes in the groundwater table only through the margin of surface water deliveries. While we cannot directly test this assumption, we believe it is plausibly true since allocations, to our knowledge, are not used for anything other than determination of surface water deliveries. The second assumption relates to the relevance of the instrument. Results from the first-stage are presented in table A1 and show that allocations are a strong instrument for deliveries. We present both the reduced-form (outcome regressed on allocations) and the instrumental variable results for each set of results.

Other threats to identification stem from regional time-varying unobservables that correlate with both changes in water allocations and changes in the depth to the groundwater table. Our inclusion of local precipitation as a control is motivated by this concern. We assume that, conditional on a rich set of fixed effects and controls for localized weather shocks, time-varying unobservables that impact changes in the groundwater table are not correlated with surface water allocations. Given that annual allocation percentages are determined by an algorithm based on environmental conditions and reservoir levels, this is plausible to assume. Insensitivity of the treatment effect to the inclusion and exclusion of time-varying local weather shocks included in X_{it} lends support for this assumption.

Outcome 2: Domestic Well Failures

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

$$\begin{aligned} Y_{it} &= \beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + B'X_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \\ SWD_{it} &= \gamma_1 SDA_{it} + + \gamma_2 HDD_{it} + \Gamma' X_{it} + \lambda_t + \alpha_i + \mu_{it} \end{aligned} \tag{6}$$

where Y_{it} is now a binary outcome indicating a reported well failure. The coefficient estimates of interest from this equation, β_1 and β_2, represent the the change in likelihood that a domestic well fails in a given year when surface water availability and extreme heat change, respectively. The independent variables, SWD_{it} and SWA_{it}, represent surface water deliveries and allocations in AF per acre, respectively. HDD_{it} reports the number of harmful degree days at well i in year t. The vector X_{it} controls for other localized weather shocks. Annual fixed effects, λ_t, control for statewide dynamic shocks, like statewide policy or state-level drought.

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

Outcome 3: Agricultural Well Construction

Our final outcome of interest is new agricultural well construction. We focus on well construction because it is the one observable mechanism that contributes to the reduction in groundwater tables. New agricultural wells represent the observable extensive-margin response that complements the unobservable intensive-margin response of increased pumping. To estimate the effects of drought and surface water curtailment on agricultural well construction, we estimate two different specifications using our panel that is constructed at the Detailed Analysis Unit by County (DAUCO) and annual level. First, using an instrumental variables approach with two-way fixed effects, we estimate equation 7:

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

All variables are defined as before except now the variable Y_{it} measures the count of new agricultural wells where i signifies the DAUCO and t denotes the year between 1993 and 2020, and α_i represents unit fixed effects, which control for DAUCO-level time-invariant factors like area size and location. All regressions are weighted by crop acres, which identifies the weighted average treatment effect across California crop acres.

Because Y_{it} reports the non-negative count of new agricultural wells and suffers from overdispersion, we supplement this by deploying a control function approach with fixed effects estimated with Psuedo-Poisson Maximum Likelihood (PPML) (Wooldridge, 2015). We estimate the Poisson model with equation 8, our preferred specification:

$$\begin{aligned} E[Y_{it}|SWD_{it}, \mathbf{X}_{it}, \alpha_i, \lambda_t] &= \exp\{\beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + \mathbf{B'X}_{it} + \alpha_i + \lambda_t + \phi \hat{\mu}_{it}\} \\ SWD_{it} &= \gamma_1 SDA_{it} + \gamma_2 HDD_{it} + \Gamma' X_{it} + \alpha_i + \lambda_t + \mu_{it}. \end{aligned} \tag{8}$$

This method also allows us to test for endogeneity of the regressor by including $\hat{\mu}_{it}$ in the second-stage. The coefficient on $\hat{SWD}_{it}$ indicates that for every one AF decrease in surface water deliveries, the number of new agricultural wells will change by $e^{\beta_1} - 1$ percent. Similarly, for every additional harmful degree day, $e^{\beta_1} - 1$ percent more agricultural wells will be constructed.

6 Results

Results from the estimation of equation 5 are reported in Table 3. Columns (1) and (2) report results from the reduced-form effect of per-acre allocations on the change in groundwater depth with and without controls for local weather. Columns (3) and (4) present IV results where allocations are used as an instrument for surface water deliveries. All specifications include time and well fixed effects. In our preferred specification in column (4), we further condition on local weather variables contained in X_{it}.

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

IV results in columns (3) and (4) demonstrate that allocation-induced changes in surface water deliveries and extreme heat have a negative and significant effect on the groundwater table. Our preferred estimates in column (4) of Table 3 imply that a one AF reduction in SW deliveries leads to 3.75 ft decline in the groundwater levels. Results are stable to the inclusion of additional weather controls. We see that groundwater depth is also responsive to extreme heat, with groundwater levels declining by 0.04 ft for every additional harmful degree day. Even holding constant changes in surface water supplies, additional heat is leading to a reduction in the groundwater table. This is likely due to increased groundwater extraction through both intensive and extensive margin adjustments.

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

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-2.263**	-1.627*		
	(0.807)	(0.750)		
Ag SW Deliveries (AF/ crop acre)			-4.953**	-3.753*
			(1.609)	(1.618)
Harmful Degree Days		0.0482*		0.0373*
		(0.0219)		(0.0169)
Observations	575,478	575,324	561,170	561,016
N Groups	98,097	98,077	83,789	83,769
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 change in the depth to the groundwater from the surface (ft) from 1994-2021 at the monitoring well level. Columns (1) and (2) report results from the reduced-form OLS model. Columns (3) and (4) report the second-stage IV results, where Ag surface water allocations are used as an instrument. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

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

This degradation of the groundwater stock, which manifests through changes in the depth to the water table, creates externalities for other users of that resource. In this context, the external costs imposed by groundwater pumpers who are adapting to changes in heat and surface water scarcity are borne by all neighboring users and future users of the groundwater. This externality disproportionately puts household users of groundwater at risk since domestic wells are generally drilled shallower on average and are more susceptible to well failure.

To explore this, we estimate a panel linear probability model, where *failure* is a $\{0,1\}$ outcome variable in a given year for all domestic wells in California. Table 4 displays the results from the estimation of equation 6. Columns (1) presents the reduced-form effect of per-acre allocations and heat on probability of a well failure with time and well fixed effects using data from 2015 to 2020. Column (2) includes local weather controls and includes 2014 in the sample.[9] Columns (3) and (4) show the same specification but now instrument for per-acre surface water deliveries with allocations, with column (4) showing the results from using the full sample of years 2014-2020. Across all specifications, extreme heat significantly increases the likelihood that domestic wells fail. Our preferred specification in column (4) implies that an additional harmful degree day increases the probability that a well fails by 0.2%. That specification also displays that a 1 AF reduction in surface water per crop acre increases the likelihood of local domestic well failure by 5%. These estimates are large marginal effects relative to the weighted mean probability of well failure displayed in Table 2.

Our final set of results explores one mechanism by which agricultural groundwater users are responding to heat and surface water scarcity: the construction of new wells. We start again by showing the reduced-form effect of surface water allocations on new well construction in Table 5, using both OLS and PPML to account for the fact that our outcome of interest is a count variable. Columns (1) and (2) show the simple two-way fixed effect OLS results with and without local weather controls, respectively. Columns (3) and (4) show results from the PPML estimation, where the final specification conditions on local precipitation and growing degree days. Results in column (4) imply that a one AF decline per crop acre in California, all else equal, leads to approximately 24.2% increase in the annual number of new agricultural wells drilled. While every additional harmful degree day causes an approximate .9% annual increase in new agricultural wells.

While Table 5 displays the response to an exogenous surface water allocation shock, surface water allocations may not represent actual scarcity. Producers and irrigation district may choose to receive more or less surface water throughout the year, complementing their allocations with additional deliveries from purchases from the spot market for example. The endogenous choice to

[9]Columns (1) and (3) use data from 2015 through 2020. The voluntary household system was introduced early in 2014 and may have not been a widely known reporting tool for households across the state. This could explain why the point estimates for surface water are smaller in magnitude and less precise when including 2014.

Table 4: Linear Probability of Reported Well Failure

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

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

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

adjust deliveries during a drought year may attenuate the reduced-form estimates in Table 5.

Table 6 reports the estimates of new agricultural well construction on surface water deliveries, where surface water deliveries are instrumented by allocations. Columns (3) and (4) are estimated using a control function approach with a linear first stage and PPML in the second stage. As expected, the estimate on surface water deliveries is larger than the corresponding reduced-form estimate in Table 5 and implies that the extensive-adaptation response is approximately 46.2% increase in new agricultural wells.

One concern is that farmers are simply moving their well drilling forward in time instead of increasing the total number of wells drilled. A concern with this kind of inter-temporal substitution is that this specification, which focuses only on the contemporaneous effect, would be overestimating the treatment effect. Tables A2 and A3 in the Appendix consider the dynamics of agricultural

Table 5: Construction of New Agricultural Wells: Reduced-Form

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

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

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

well drilling and provides evidence to suggest that the contemporaneous effect is capturing the bulk of the response.

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

7 Discussion

The impacts of climate change depend on the extent to which individuals adapt. While climate adaptation by some may limit their own potential damages from extreme heat and precipitation variability, these adaptive measures may unintentionally impose costs on others. In this paper, we show that agricultural producers in California significantly adapt to added heat and reduced

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

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

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

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

surface water through the channel of constructing new agricultural wells. We also show that local groundwater levels are responsive to these annual fluctuations in weather. These climate-induced changes deplete local groundwater resources, imposing externalities on other users of groundwater. Negative externalities arise for rural communities through the channel of domestic well failures and subsequent reductions in drinking water access.

These findings contribute to the knowledge of the impact of climate change in three ways. First, we show that producers in California spend approximately $37 million annually for every AF per crop acre reduction of surface water availability. While irrigation may mitigate agricultural yield and revenue damages, climate change still imposes a significant annual cost to irrigated agriculture. Second, adaptation strategies contribute additional burden on those less able to engage in adaptive behavior. These externalities of adaptation have traditionally been ignored in calculating the economic costs of climate change but should be taken into account for a more complete accounting of climate change damages. Importantly, these externalities are borne in low socioeconomic communities, increasing environmental inequality. Results are relevant for policymakers seeking to implement environmental regulation.

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Appendix

Table A1: Agricultural SW Deliveries: First-Stage Results

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

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

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

Tables A2 and A3 consider the dynamics of agricultural well drilling. In Table A2, we report the results from equation 7 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 A3 similarly considers the dynamic effects on new agricultural well construction but instead focuses on the reduced-form effect of surface water allocations with the Poisson transformation. This is because the control function approach outlined in equation 8 is incompatible with lagged variables that enter nonlinearly. A look at the coefficients on lagged surface water supplies across all specifications reveals no consistent pattern. The sum of the coefficients, which captures the effect of a single supply shock over time, are not statistically different from each other across specifications. This suggests that the contemporaneous effect is characterizing the most meaningful impact of year-to-year changes in water supplies on new agricultural well construction.

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

On the other hand, it may be the case that farmers are simply shifting forward in time the decision to drill a new well. A behavioral response that only consists of inter-temporal substitution would suggest that coefficients on lagged variables should take the opposite sign of the contemporaneous effect, because drilling a well today reduces the need to drill in the future. This in turn would cause the sum of the coefficients to attenuate as we add more lagged variables. Since we see no observable trend from the inclusion of the lagged variables, it suggests that neither of these forces are dominating. These two effects are working in opposite directions and cannot be teased out. Taken together, this pattern of results on lagged variables support our main results reported in Table 5. The vast majority of the effects of drought on well construction are concentrated in the first year. We proceed by focusing on the more parsimonious specification of equation 8 and retaining power with more observations.

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

Table A2: Lagged Agricultural Well Construction

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

Note: Table reports regression results from the estimation of equation 7. The dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

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

Table A3: Lagged Agricultural Well Construction

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

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

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

Table A4: Lagged Changes in Groundwater Depth

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

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

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

Table A5: Lagged Probability of Well Failure

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

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

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

Table A6: New Constructed Well Depth

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

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

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

Table A7: Construction of New Domestic Wells

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

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

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

Table A8: Construction of New Agricultural Wells: Municipal and Industrial Surface Water

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

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

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