The benefits and costs of agricultural adaptation to surface water scarcity

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Abstract

Farmers can avoid a large amount of climate-related production losses through adaptation, but if they adapt in socially costly ways, like groundwater intensification, the benefit of adaptation becomes less clear. In this paper, I study how farmers in California adapt to surface water scarcity, and I quantify the value of that adaptation. I exploit variation in surface water delivery forecasts and forecast updates across irrigation districts within years to identify farmers' adaptation strategies. The results reveal that farmers adapt with both water-conserving crop choice practices and water-intensifying well drilling and extraction practices. However, I find that groundwater intensification far outpaces conservation. Further, low surface water availability accelerates well drilling by several years, which induces a transition to even higher water intensity crops, resulting in persistent and magnified social costs. To estimate adaptation's overall private benefit, I extend the standard conceptual and empirical framework to accommodate multiple intra-annual adaptation decision periods. I find that adaptation to water scarcity significantly increases farm profit when adaptation occurs early in the year, though the effect diminishes as the realization of surface water availability approaches. Overall, in California, the externalities of adaptation are about 25% as large as the private benefit, diminishing the gains from adaptation. My paper highlights that abstracting away from the actual decisions could result in severely overvaluing adaptation.

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After decades of academic debate, the literature has converged on the conclusion that climate change will severely damage agricultural production (Schlenker and Roberts (2009), Costinot et al. (2016), Hultgren et al. (2022)). The answer to the related, and equally important, question about how much farmers can adapt to a changing climate is unclear at best, and contradictory at worst. Papers studying adaptation in aggregate have found moderate (Hultgren et al. (2022)) to no (Schlenker and Roberts (2009), Burke and Emerick (2016)) ability to avoid losses, while papers studying specific adaptation actions find that farmers do respond to weather or drought shocks (Hagerty (2022), Burlig et al. (2024)). Farmers' responses sometimes make them more resilient to weather damage (Auffhammer and Carleton (2018), Michler et al. (2019)) and sometimes make them more sensitive to weather and water scarcity in the long run (Hornbeck and Keskin (2014), Fishman (2018)). In this paper, I seek to unify the themes in the literature by connecting adaptation actions to the value of adaptation. In settings with perfect information and no pre-existing distortions the specific adaptation actions do not matter for economic value because farmers' maximized profits are the social benefit, regardless of the adaptation action (Carleton et al., 2024). In agriculture however, among other distortions, farmers often adapt to surface water scarcity using a partially non-renewable common pool

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groundwater resource (Fishman, 2018)[1]. I study the context of farmers in California who irrigate intensively with groundwater in years with low surface water, leading to a rapidly depleting aquifer (Jasechko et al. (2024), Department of Water Resources (2025a)).

In the presence of groundwater extraction externalities, the actions that farmers take in response to surface water scarcity informs us about the social value of adaptation. When surface water availability is low, farmers might choose to conserve water, or substitute toward groundwater by extracting from existing wells and drilling new wells. Although farmers take the action with the highest private benefit, the social costs vary among the options leaving the net social benefit of adaptation unclear. Furthermore, the private value of the choices depends on the timing of information and previous adaptation decisions. Farmers make choices sequentially within a year (Antle, 1983) so that early choices (like cropping) determine the choice set and values of alternatives (fallowing vs groundwater extraction) later in the year. Long-term adaptation strategies like well drilling permanently alters the value of alternative adaptation choices, since well drilling lowers the marginal cost of groundwater use. Understanding the patterns of adaptation to surface water scarcity is important since groundwater basins remain unmanaged and precipitation is decreasing and becoming more variable in many irrigation-reliant regions like California (Chandanpurkar et al., 2025).

In this paper, I ask the broad question "how do farmers adapt to surface water scarcity, and what are the consequences of that adaptation?" I answer the question in four steps. First, I study whether farmers in California make water conserving (crop choice and land fallowing) decisions and/or water intensifying (well drilling and groundwater extraction) decisions in response to surface water scarcity information learned within a year. Then, I study how the long-term adaptation option, well drilling, affects later adaptation decisions. Next, I estimate the overall private benefit of short and long-term adaptation. Finally, I compare the private benefits with my estimates about the increases in water use from adaptation to suggest how the private and social value might compare and be changing over time.

To explore how farmers adapt to water scarcity in the short run (within a year), I design my empirical framework to account for sequential decisions. Short run adaptation in agriculture is characterized by decisions with fixed lead times, made as weather and water availability in the growing season becomes more certain. I use a conceptual model to show that a simple econometric model that includes the baseline surface water availability forecast and adjustments allows me to estimate the actions taken due to information available at different times. Therefore, I need variation in surface water availability across units revealed over the agricultural season.

In my context, I leverage the differences in surface water allocation forecasts to empirically identify different adaptation actions over time. In California, over 200 water districts have contracts for surface water deliveries in the dry summer growing season. The governments that run the infrastructure projects announce initial surface water forecasts around the early planting season, and update their projections over time. Because of exogenous differences in snowpack which differentially fill reservoirs, different districts receive different forecasts and updates over the year. I construct a panel of the most recent forecast known at three points in the year: the early planting season, mid planting season and late planting season, which spans from 1967 until 2022. I then regress adaptation actions (crop choice, crop fallowing, well drilling and groundwater extraction) on the surface water availability announced in each of the three periods.

I find that short-term water information affects all decisions that I study. A one-point decrease in the

[1] Other reasons for studying adaptation actions include choice sets being constrained (like in development contexts), so that offering new means of adaptation can be beneficial (Macours et al., 2012). Another is imperfect information or imperfect beliefs (Kala, 2017)

surface water availability in each point in the planting season shifts farmers toward water conservation by idling crops and planting less water intensive annuals. At the same time, this bad surface water news shifts farmers toward higher groundwater extraction and more well drilling. Put in terms of changes in water use, I estimate that groundwater intensification increases through groundwater extraction five times more than it decreases through water conservation. The coefficients on the different periods in the year show that farmers adapt to surface water news at a similar rate throughout the season, with the exception of well drilling which diminishes as the dry season approaches. Separating the effects by positive and negative surface water availability updates ('good' and 'bad' surface water news), I find that the coefficient estimates are much larger in magnitude for news about decreasing surface water, showing that over time there is a net increase in groundwater use from these short-term adaptation actions.

For the second step of the analysis, I study how adaptation changes over time as farmers take the capital-intensive well drilling option. There are many potential avenues to explore, and I focus on four. In the first, I learn about how much earlier wells are drilled due to short-run surface water shocks using local projections (Jordà, 2005), in order to explain the well drilling choice. Well drilling in response to short-run surface water shocks makes the most sense if wells are increasing in value generally, and surface water scarcity causes some already relatively high well values to cross the threshold of profitability a few years early[2]. Then, I see how previous well drilling affects the sensitivity of adaptation actions to surface water scarcity by interacting the lag of the cumulative wells drilled in a district with the three periods of surface water information from the main estimating equation. Afterward I study how groundwater extraction increases due to new wells using exogenous changes in well drilling costs unrelated to groundwater depth as an instrument for new wells. Thus, I estimate the increases in extraction for the subset of farmers with a well value somewhat close to the threshold of drilling, in a year where surface water scarcity is not necessarily high. The local average treatment effect captures how the farmers likely to drill a well in the coming decades might act in an average water year. Finally, I explore the path dependence of future adaptation decisions through how farm cropping decisions change solely from the fact of having a well. To avoid the simultaneity of cropping and well decisions, and since crop choice might not respond in the current year, I use the same instrument within a local projections framework (Jordà et al., 2015).

Overall, I find that past well drilling decisions change the way that farmers adapt. First of all, in response to surface water shocks, wells are drilled about four years earlier that they otherwise would have been, which fits the narrative of a modest change in well value for farmers with values close to the threshold for drilling. Although the increase in wells relative to the counterfactual is temporary, the shift forward in time represents a real social cost if wells imply an increase in groundwater use[3]. From the heterogeneity analysis, I find that wells change annual adaptation behavior in two ways. Wells especially decrease the amount of ex-ante adaptation, suggesting that the value of preparation decreases. Second, water conserving practices tend to decrease overall, while groundwater extraction increases at the time of the surface water allocation realization. The instrumental variables specification confirms that groundwater extraction increases the year when a well is drilled, even though the local average treatment effect does not estimate the groundwater use

[2]In California, it is likely the case that well values increased cover time. Crop output prices increased, well technology improved, and average surface water availability decreased over my period of study.

[3]While the aquifer remains unmanaged, users extract until the marginal benefit of water use is driven down to current extraction cost, rather than rising at the rate of interest as Hotelling's rule (or a modified rule with partial recharge) prescribes. As a result, the shadow value of the groundwater stock is far below the efficient level, and this gap widens as the aquifer is depleted. Therefore, faster depletion implies that by the time the aquifer is managed, the value of the stock will be even lower than if a well was not drilled four years early.

increase in years only when surface water scarcity was high, most likely implying that since surface water is both constrained and has an artificially low price, water use will increase when wells are drilled even though groundwater is more expensive. Last, I find that farmers increase agricultural land area, and high-water crop acreage, particularly in perennials, after drilling 'surprising' new wells. In all, my results point to the investment in well capital leading to increases in groundwater extraction along several margins.

In the final portion of my analysis, I study the net benefit of the adaptation decisions. The conceptual framework in the literature shows that we can estimate the value of adaptation by regressing outcomes like profits on both forecasts and realizations (Shrader, 2023). I extend the conceptual framework to include the sequential decision making and ex-post adaptation characteristic of the agricultural context. I show that in a regression of profits on my the three periods of surface water forecasts, each coefficient on information represents the value of the decisions taken in that period, which includes both the unanticipated actions taken and the planned future actions decided upon in the current period. Since I previously found that wells diminish the value of preparatory action, I conduct a heterogeneity analysis where I interact the surface water information with the lag of the cumulative wells.

I find that the most beneficial adaptation occurs early in the planting season, prior to the first surface water allocation forecast. Through adaptation, farmers can virtually insulate themselves from the direct effect of surface water scarcity. I also find that these specific surface water allocation forecasts have value, meaning that historically these forecasts have had information in them, and that adjusting forecasting policy might affect farmers outcomes.

Overall, I estimate the permanent increase of groundwater use due to a one-time moderate surface water allocation decrease to be about 0.04% from baseline. I monetize the social cost using groundwater tax rates proposed by the Sustainable Groundwater Management Act, designed to limit groundwater extraction to safe yield, as a proxy for the common-pool externalities. Overall, this one-time marginal surface water shock has a social cost of about $4 million 2017 dollars summed across all water districts in the study. The social costs make up about 1/4 of the private benefits of adaptation. My results show that the social costs of adaptation might make up a substantial portion of the private benefits of adaptation. In contexts with unmanaged resources, relying on private actors to address the consequences of climate change may create future problems of resource depletion.

This paper contributes to the growing literature on forecast-enabled ex-ante adaptation, which demonstrates that anticipatory responses substantially reduce weather-related damages (Molina and Rudik (2022), Shrader et al. (2023), Downey et al. (2023), Shrader (2023)). I explicitly link the value of adaptation to the specific actions people undertake. While previous research has identified the behavioral mechanisms underlying adaptation benefits, such as Shrader (2023) who shows that fishers reduce production costs after adverse El Nino forecasts, I extend my analysis to adaptation actions with diverse characteristics, including externalities and permanence. These features introduce social costs and long-term consequences that complicate the traditional narrative of the benefits of ex-ante adaptation to short-term weather.

I also build on the prior work of Anand (2023), who finds that earlier information significantly reduces traffic mortality during extreme winter. I provide complementary evidence that longer forecast leads increases the value of adaptation, while revealing that individuals fundamentally alter their adaptation strategies at different time horizons. This finding, like Anand (2023), challenges the theoretical model of Millner and Heyen (2021) which suggests that long-run predictability becomes irrelevant when people can continuously adjust their actions. In contrast, since the available set of adaptation options evolves as a forecasted event approaches, long-term predictability becomes crucial when some adaptive measures have social costs or are irreversible. Finally, while Burlig et al. (2024) show that farmers in India tailor investments to monsoon forecasts given their stated prior beliefs, my research highlights the critical limitations that emerge when forecasts arrive too late for optimal adaptation.

I also add to the literature on adaptation to climate change in agriculture. There are two main bodies of work. The first studies adaptation in aggregate, using the methods in the climate econometrics literature, including cross-sectional analyses and long differences, to identify how climate damages are lessened through adaptation (examples include Mendelsohn and Dinar (2003), Burke and Emerick (2016), Hultgren et al. (2022)). The second strand of literature studies specific adaptation choices, either exploring the choices that farmers make (Hagerty (2022), Burlig et al. (2024), Blakeslee et al. (2020)), or how farmers' choices can lower their sensitivity to weather shocks (Michler et al. (2019), Auffhammer and Carleton (2018)) or increase their sensitivity to weather shocks through groundwater investment (Fishman (2018), Hornbeck and Keskin (2014)). My paper bridges the literatures by combining what choices are being made with the value of those choices.

In the first vein, Hagerty (2022) finds that farmers fallow land in response to short-run water scarcity and transition land out of agriculture in response to water scarcity, Burlig et al. (2024) finds that farmers use a variety of strategies in response to monsoon forecasts including changing cultivated area, crop type, and farm inputs, and Blakeslee et al. (2020) finds that farmers in India facing long-term water scarcity shift a portion of their income to non-agricultural work. In the other vein, Michler et al. (2019) finds that conservation practices can diminish farmers' sensitivity to deviations in rainfall, (Auffhammer and Carleton, 2018) finds

I also add to the literature on institutions governing water management. A growing literature explores California's complicated water regime (Hagerty and Bruno (2024), Ayres et al. (2021), Hagerty (2023)), which is economically relevant because the state produces more agricultural output (in dollars) than any other (Ruth, Timothy, 2017). My paper studies the surface water allocation forecasts specifically, which concerns a substantial amount of annual agricultural water. I also add to the literature in water economics on the substitution between groundwater and surface water (Burt (1964), Ferguson (2024)) which is important because of the wedge between the private and social benefit of these resources. Bruno et al. (2024) documents the same mechanism for substitution that I do, where surface water delivery quantities affect the number of wells drilled in California. Since information provision can affect adaptation choices even before regulation is in place, my paper is policy relevant because many aquifers globally lack regulation (Jasechko et al., 2024), as California's did until recently (Hagerty and Bruno, 2024).

Finally, I contribute to the agricultural economics literature on sequential and intra-annual decision making, which has long recognized that farmers' choices are best understood as multi-step processes that evolve as new information becomes available throughout the growing season (Antle, 1983). However, I contribute a rare empirical study in this literature, confirming with a real-world case the intuition that adaptation choices change over the growing season because of previously fixed decisions (Ortiz-Bobea, 2021). Understanding sequential decisions and adaptation will become more important as weather and water conditions become more volatile.

The paper proceeds as follows. Section 2 covers the essential background for this paper, while section 3 extends the conceptual framework in the literature to the agricultural context. Section 4 describes the data sources I use. In section 5 I estimate the timing of different adaptation decisions, as well as the static social costs of adaptation. In section 6 I estimate the aggregate benefits of adaptation. Section 7 describes the dynamic social costs of the adaptation decisions stemming from well drilling, and section 8 concludes.

1 Background

1.1 California's agriculture and climate

Ample sunlight, mild winters and fertile soil makes California a major supplier of permanent crops like tree nuts and citrus (2/3rds of the US total) and other high-valued crops like vegetables and berries (1/3 of the US total), primarily in an inland region called the Central Valley (Ruth, Timothy (2017), California Department of Food and Agriculture (2023)). However, agricultural water demand and the natural water availability are mismatched. The majority of the state's precipitation (75%) falls north of the Central Valley, and the majority of the Central Valley's precipitation falls between October and April (90%), which is outside of the hot summer months and the main fruiting season, when crop water demands are the highest (CA State Climatologist, 2025). Therefore, agriculture in California depends on irrigation, facilitated by large infrastructure projects for the storage and conveyance of surface water, and also private groundwater access. California uses more irrigation water in agriculture than any other state (16% of the nation's total), and the majority of irrigated land is in the Central Valley (75%) (US Geological Survey (2025), Dieter et al. (2018)).

Despite the high presence of permanent crops, more than 2/3rds of California's irrigated acreage is devoted to growing annual crops, allowing farmers the opportunity to make different planting decisions yearly (Bauer, 2022). Because of the long growing season, annual crops are planted at various times throughout the year. Typically, cool season crops are planted either between December and February, or July and September, while warm season crops are planted between March and June. Grains are usually planted in the fall, from October to December. High summer temperatures make the average crop water requirement for warm weather crops much higher than cool weather crops, though there is a lot of variation between annuals planted at the same time[4]. Farmers in Central California have commonly used crop switching for drought management (Visser et al., 2024).

1.2 Surface water projects and surface water allocation forecasts

The state of California and the US Bureau of Reclamation each built systems of reservoirs and canals between the 1930s and 1960s for flood control and water delivery across California. These state and federal water infrastructure projects are referred to respectively as the State Water Project (SWP) and Central Valley Project (CVP). These projects deliver a substantial portion of their water to agriculture (one-third of SWP, and one-half of CVP), and combined deliver about 19% of the water used in agriculture yearly (Bureau of Reclamation (2024), Department of Water Resources (2024)). Irrigation districts gained access to a set delivery quantity from these projects by signing long-term contracts in the 1960s, in return for covering capital and operating costs. Through these arrangements, districts with project contracts have received heavily subsidized surface water (Sharp and Carini, 2004). The majority of water districts charged agricultural users less than $50/ acre foot for surface water in 2021, and many paid much less, while groundwater rates tend to be higher, and the market rate for surface water higher still[5] (Aquaoso (2021)).

[4]For example, though they are both warm season crops, cotton requires almost three times as much water to grow as dry beans.

[5]Burlig et al. (2020) estimates the average marginal cost of groundwater to be $50 an acre foot, though a short survey of agricultural districts groundwater rates suggest that groundwater is usually a bit more expensive, around $200, which is 2-3

However, the amount of surface water that projects are able to deliver varies from year to year because of the variability in snowpack in the Sierra Nevada mountains, which supplies the majority of the water in California's developed surface water infrastructure (Soderquist and Luce (2020), de Guzman et al. (2022)). Specifically to aid agricultural decision makers, the Department of Water Resources and Bureau of Reclamation publish a forecast at the start of the planting season for the percent of a district's surface water contract their projects are expected to fulfill[6] (USBR, 1992). Updates to the initial surface water delivery projection are announced irregularly until the final delivery percent is finalized in May or June at the start of the dry season. I call the series of project forecasts "surface water allocation forecasts", and the final realization the "final surface water allocation". Despite the surface water allocation forecasts coming from different agencies, they have similar characteristics, and follow similar methodologies due to the joint administration of the water projects (US Bureau of Reclamation and the California Department of Water Resources, 1986). Appendix figure A.1 shows examples of what the surface water allocation forecasts have looked like through time. The forecasts have been disseminated through newspapers, bulletins, and websites. Low surface water allocation forecasts are especially salient, making front page news in many agricultural communities. Figure A.2 further shows the importance of the surface water allocation forecasts to water users. Out of all water-related news topics in California published by the Department of Water Resources and the Bureau of Reclamation, the highest median page views are for surface water allocation announcements.

The other major source of agricultural surface water in central California comes from streamflow originating in the Sierra Nevada. Irrigation districts and other public entities hold the vast majority of these legal diversion rights (81% of water), obtained from the State Water Resources Control Board[7] (Grantham and Viers, 2014). Although on paper, these rights operate on a system of priority, because of a lack of monitoring and enforcement, rights holders in the same watersheds will face similar streamflow shocks in the same year (Weiser, 2014).

1.3 Well drilling and groundwater

Groundwater supplies 40% of agricultural water in regular water years, and substantially more in dry years (Greenspan et al., 2024). The Central Valley aquifer is the second-most utilized in the United States, where on average 2.4 million acre-feet more water was extracted annually than was recharged(US Geological Survey, 2025). The severity of the overdraft has resulted in concerns about groundwater depletion and other externalities including saltwater intrusion (Goebel et al., 2019), arsenic contamination (Smith et al., 2018), infrastructure and property damage through subsidence (Borchers et al., 2014), an increase in the future costs of extraction, and a permanent decrease in aquifer storage capacity (Smith and Majumdar, 2020), in addition to the standard common pool externality. Nevertheless, until 2014 only 7% of the state's groundwater basins had defined property rights, none of which were in the Central Valley (Ayres et al., 2018). The California legislature passed the Sustainable Groundwater Management Act in 2014 to address unsustainable groundwater extraction, though no anticipatory responses have been detected through 2022, and many of the Central Valley's regulated basins failed to meet the act's guidelines for management planning

times districts' surface water rates. The surface water market price can fluctuate dramatically, from $150 in wet years to $1300, as proxied by the Nasdaq Veles water prices index.

[6]The intention is clearly stated in the CVP operations criteria: "all of the agricultural contractors need to know about their water allocation as soon as possible so that they can make timely decisions and appropriate plans for using their allocated water supply." (USBR, 1992)

[7]Individuals hold less than 1% of water.

through 2024 (Bruno and Hagerty (2024), State Water Resources Control Board (2024).

To access groundwater, farmers can drill private wells. The State Water Resources Control Board has required well drilling permits since 1990, which imposed a time delay on drilling[8] (GEI Consultants, 2017). While physically drilling a well takes only a week, permitting and demand queues delays drilling by one to six months[9]. Well drilling is a moderate investment for most farms. Agricultural wells in the last decade have typically cost between \$50,000 and \$500,000, which is between 25% and 250% of the average farm's yearly income (Smith (2014), United States Department of Agriculture (2022)).

1.4 Combining the background

In this section, I combine the pieces of the farming context in California to explain why surface water supply shocks at different times of the year could result in different margins of adaptation with different private and social costs. Whether and when farmers actually respond to short-term water supply information with these actions is the empirical question I answer in later sections.

Farmers in California seek to maximize their lifetime profits by producing crops. Every year, farmers face a long agricultural season with several decision periods. There is an early planting season, spanning from October to January, a mid planting season, spanning from February to March, a late planting season, running from April to May, and a dry season spanning June to September. In each of these periods, farmers receive new information about surface water available to them in the dry season, which becomes more accurate as the dry season approaches. Surface water and groundwater are perfect substitutes that are essential inputs to crops. Surface water is always the least expensive option for irrigating their crops, and groundwater is only available if the farmer has invested in a groundwater well. There is also a backstop source of water on the surface water market which is significantly more expensive than groundwater.

In each planting period, farmers make a variety of decisions, some of which are short-run and only have consequences within the current year, and some of which are long-run, having consequences across years. The first option is crop choice. Farmers choose to plant any portion of her unplanted fields with annual crops or permanent crops suited to planting in that period. Once a field is planted, that field cannot be planted with another crop until the following year (for annuals), or until the year after abandonment (permanent crops). Crops differ in characteristics by their profitability and water intensity. Although every planting period has crops of a variety of water intensities, on average later planting periods have crops of higher water intensities. Second, farmers can also choose to drill a well to access groundwater. The cost is a one-time fixed cost of well installation, which varies with depth to the water table and the capacity of the well, and is usually substantial relative to a farmer's income. The benefit of a well is the sum of discounted additional profits from having access to groundwater forever, which is determined by the long-run expectations of dry-season surface water. Importantly, the irreversibility of the fixed costs of investment, plus the uncertainty of future surface water availability means there is an option value of drilling. A well can be drilled anytime, but there is a delay between making the drilling decision and having access to groundwater ranging between 1 and 6 months, where the probability of longer delays increases during drier years. Third, farmers can choose to extract more groundwater using wells that they already have, up to the capacity of their well, paying a per-unit cost of extraction, typically only from the electricity cost to run a well pump. Finally, in every

[8] Permits are virtually always granted.

[9] From the testimonies of two well drilling contractors.

period, regardless of past decisions, farmers can choose to abandon crops by ceasing to water what was already planted.

At different times within a year, the choice set changes due to timing constraints and previously fixed decisions, which has implications for the private and social value of those choices. Conditional on the year's dry-season surface water availability, receiving accurate dry-season surface water information earlier is always more privately beneficial, because there are more adaptation options to choose from, and the decisions would be better tailored to actual water conditions. By the time the dry season arrives, the only options left for adjusting to surface water supply shocks are crop abandonment, groundwater extraction, and well drilling, though the well would likely not even be available for use in the current year. The well value changes throughout the season for two reasons. First, the probability of being able to use the well in the current year decreases. Second, the short, medium run and long-term surface water availability becomes more certain, affecting the direct expectations of the value added of the well, as well as the option value. Which effect dominates is an empirical question.

In periods of the year when well drilling and groundwater extraction are chosen relatively more, the social cost of water supply shocks is higher because of the resulting increases in groundwater withdrawn which has large unpriced externalities. The social costs of the two differ because a new groundwater well likely has a permanent effect. Not only will groundwater be applied on the current crop mix, but having a well influences future cropping decisions by decreasing the marginal cost of water in dry years, which could result in an even greater amount of groundwater used. The size of the externality depends on when the well would have been drilled otherwise (i.e. how long the well remains excess). On the other hand, crop choice has low social costs. Because surface water is allocated to rights holders and contract holders, tailoring crops to the level of surface water available allows farmers to maximize private benefits without imposing costs on other users of the water.

In table 1, I summarize the time periods, climate, government actions, information available, decisions available, and costs and benefits of the remaining decisions, as outlined in the conceptual framework and background, for farmers in water districts with contracts to surface water projects. The table highlights how the responses to water information and consequences of those responses evolve within a year because of changing constraints.

2 Conceptual framework

Here I describe my conceptual framework for fixing ideas. This framework builds upon Shrader (2023) which shows how to identify the benefits of adaptation to forecasts from observable, ex post data. I expand upon this by accounting for sequential decisionmaking that occurs before and after observing the forecast and realization of weather.

2.1 Baseline framework: only ex-ante adaptation

I first begin with re-casting the original Shrader framework for my setting. Expected profit-maximizing farmers take ex-ante adaptation actions a_{early} given expectations about surface water shortfall $\hat{s}$. Thus, farmers choose a^*_{early} by:

Table 1: Timeline of agricultural decisions, costs of decisions, climate, and government actions

Season	**Early planting**	**Mid planting**	**Late planting**	**Dry season**
Months	Oct - Jan	Feb - Mar	Apr - May	Jun - Sep
Climate	Rainy, cool	Rainy, cool	Some rain, warm	No rain, hot
Government action	None	- Provide surface water allocation forecast	- Provide surface water allocation forecast	- Deliver surface water to districts
Info available	- Last year's water availability - Weather forecasts	- Early surface water allocation forecast - Weather forecasts - Snowpack forecast	- Mid surface water allocation forecast - Weather forecasts - Snowpack forecast	- Final surface water allocation - Weather forecasts - Final snowpack
Decisions available	- Plant early crops - Choose mid crops - Choose late crops - Drill well (likely usable this year) - Change groundwater extraction - Abandon permanent crops	- Plant mid crops - Choose late crops - Drill well (likely usable this year) - Change groundwater extraction - Abandon permanent crops - Abandon annual crops	- Plant late crops - Drill well (unlikely usable this year) - Change groundwater extraction - Abandon permanent crops - Abandon annual crops	- Drill well (unlikely usable this year) - Change groundwater extraction - Abandon permanent crops - Abandon annual crops
This year's private cost of remaining decisions	Low	Medium	Medium	High
Social cost of remaining decisions	Low	Medium	Medium	High

$$\max_{a_{early}} \quad pf(a_{early})\mathbb{E}_{t-1}[g(\hat{s})] - c_{early}a_{early}$$

Where $\mathbb{E}_{t-1}[g(\hat{s})]$ is the function representing how shortfall is expected to affect revenues. Let ex-post revenues be given by:

$$y = pf(a^*_{early})\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg) \tag{1}$$

Let $\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg)$ be the realization of how shortfall actually affected revenues, which is given by $g(s)$ in Shrader (2023). $h(\cdot)$ is a function representing the way realized damages differ from the expectation, given by $\int_{\hat{s}}^{\hat{s}+\varepsilon} g(s)ds$. I explicitly define the realized shortfall effect as a modification from the expected shortfall effect because it more easily allows me to build in sequential decision making.

In Shrader (2023) the object of interest is direct damages from shortfall, which is defined as the derivative of revenues with respect to realized shortfall, conditional on optimal adaptation. Taking the derivative of (1) with respect to $\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg)$ equals $pf(a^*_{early})$. The problem with estimating direct damages empirically by simply regressing realized revenues on realized shortfall is that realized shortfall is correlated with expected shortfall, which is correlated with expected revenues through ex-ante adaptation. The way we can address the bias is by including the expected shortfall in the regression.

I keep the assumption from the original framework that the way that the shortfall updates is unpredictable, so that $\frac{d\mathbb{E}[h(\hat{s},\varepsilon)]}{d\mathbb{E}_{t-1}[g(\hat{s})]} = 0$. The derivative of realized revenues with respect to expected shortfall is

$$\frac{\partial y}{\partial \mathbb{E}_{t-1}[g(\hat{s})]} = p\frac{df(a^*_{early})}{da^*_{early}}\frac{da^*_{early}}{d\mathbb{E}_{t-1}[g(\hat{s})]}\bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s},\varepsilon)\bigg) + pf(a^*_{early})$$

The first term gives the value of adaptation. It shows how realized revenues would have been different if the shortfall forecast was marginally higher, given the actual realization of shortfall. The second term is the same direct effect of the shortfall as given by the derivative of realized revenues on realized shortfall. Thus, including the forecast of the shortfall in the regression of realized revenues on the realized shortfall identifies both the direct effect of the shortfall and the benefit of adaptation.

2.2 Extended framework: multiple periods of adaptation

In agriculture, farmers make decisions throughout the planting and growing season. Early in the planting season, farmers have the least constraints, but also the least information. For example, in a year with a low shortfall forecasted (a high amount of surface water), the farmer might choose to plant water intensive annuals. If mid-way through the planting season she learns that shortfall is higher than she initially thought, she might stop watering some fields, or she might plan to extract more groundwater.

To incorporate intra-annual adaptation into the previous framework, I consider three decision periods in a year. In the early decision period, $\hat{s}$ is known, and a_{early} may be chosen for cost c_{early}. In decision period 2, the surface water shortfall is updated to $\hat{s}_{mid}$, and the new information in the update is $\varepsilon_{mid} \sim N(0, \sigma_{mid})$, where $\hat{s}_{mid} = \hat{s} + \varepsilon_{mid}$, and farmers purchase inputs a_{mid} for cost c_{mid}. In the late period, the realized surface water shortfall s is realized, where $s = \hat{s}_{mid} + \varepsilon_{late} = \hat{s} + \varepsilon_{mid} + \varepsilon_{late}$, and farmers can make any final input choices they would like, a_{late} for cost c_{late}. Later adaptation is less expensive than earlier adaptation because it is less constrained, $c_{early} \leq c_{mid} \leq c_{late}$.

Consider how a_{early} changes from the previous framework.

$$\max_{a_{early}} \quad pf(a_{early}, \mathbb{E}[a_{mid}], \mathbb{E}[a_{late}]))\mathbb{E}_{t-1}[g(\hat{s})] - c_{early}a_{early} - c_{mid}\mathbb{E}[a_{mid}] - c_{late}\mathbb{E}[a_{late}]$$

I put later adaptation decisions in expectation operators to signify that farmers choose inputs with some expectation about their future choices, but no certainty.

The early adaptation decision is implicitly defined by:

$$\begin{aligned} p\bigg[\frac{df}{da_{early}} + \frac{df}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + \frac{df}{d\mathbb{E}[a_{late}]}\frac{d\mathbb{E}[a_{late}]}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + \frac{df}{d\mathbb{E}[a_{late}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}}\bigg]\mathbb{E}_{t-1}[g(\hat{s})] \\ = c_{early} + c_{mid}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + c_{late}\bigg[\frac{d\mathbb{E}[a_{late}]}{da_{early}} + \frac{d\mathbb{E}[a_{late}]}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}}\bigg] \end{aligned} \tag{2}$$

The early adaptation decision is a function of the expected later choices, and the prices of those later choices. How much the later choices affect the early adaptation choice depends to the extent that the adaptation periods are substitutes and complements. If the adaptation options are substitutes (for example, planting low water annuals in the early period means that a farmer cannot plant high water annuals in the mid period) decreases the marginal revenue from adapting in the early period.

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Now, consider realized profit in the case of sequential adaptation:

$$\begin{aligned}\pi = \max_{a_{late}} \quad & pf(a^*_{early}, a^*_{mid}, a_{late})\Big(\mathbb{E}_{t-1}[g(\hat{s})] + h_{mid}(\hat{s}, \varepsilon_{mid}) + h_{late}(\hat{s} + \varepsilon_{mid}, \varepsilon_{late})\Big) \\ & - c_{early}a^*_{early} - c_{mid}a^*_{mid} - c_{late}a_{late}\end{aligned} \tag{3}$$

In the period where profits and revenues are realized, the previous stages of adaptation decisions are set. The farmer will maximize her profits by choosing ex-post adaptation a^*_{late}, which might differ from her expected choice of a_{late} because of the difference between the expected and realized shortfall.

Like in the baseline model, we can take the derivative of realized revenues or profits to understand what a regression of outcomes on the components of information can tell us. Let y again denote realized profits, and let the shorthand symbols $\hat{g}$ correspond to $\mathbb{E}_{t-1}[g(\hat{s})]$, h_{mid} correspond to $h_{mid}(\hat{s}, \varepsilon_{mid})$ and h_{late} correspond to $h_{late}(\hat{s} + \varepsilon_{mid}, \varepsilon_{late})$. In the framework in Shrader (2023), we can found the value of ex-ante adaptation conditional on the realization of surface water scarcity. When adaptation can be driven by multiple components of information, the derivative becomes complicated. It is simpler to take the derivative of the revenues with respect to each component of information, and then to rearrange. Equation (4) shows the result of taking these derivatives.

$$
\begin{aligned}
\frac{dy}{d\hat{g}} : p\Bigg[& \underbrace{\frac{df}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}}}_{\text{Ex-ante adaptation}} + \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}} + \frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}} + \frac{df}{da_{late}}\frac{da_{late}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}}}_{\text{Effect of ex-ante adaptation on later decisions}} + \\
& \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{g}}}_{\text{Mid-season adjustments}} + \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{g}}}_{\text{Mid-season adjustments on later decisions}} + \\
& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{d\hat{g}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}} \\
\frac{dy}{dh_{mid}} : \Bigg[& \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{dh_{mid}}}_{\text{Mid-season adjustments}} + \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{dh_{mid}}}_{\text{Mid-season adjustments on later decisions}} + \\
& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{dh_{mid}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}} \\
\frac{dy}{dh_{late}} : \Bigg[& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{dh_{late}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}}
\end{aligned}
\tag{4}
$$

The first term shows how realized revenues would have been different if the initial forecast was different, $\frac{dy}{d\hat{g}}$, given the later components of information h_{mid} and h_{late}. There are several channels present. $\hat{g}$ represents the effect of the early shortfall forecast on realized revenues. The early shortfall forecast affects the ex-ante adaptation in the early period, the first term. Since the early shortfall forecast affects ex-ante adaptation, it also affects later adaptation through the choice of ex-ante adaptation, which are summarized in the following three terms. The early shortfall forecast also determines the level of the shortfall in the mid-season period, and thus directly affects mid-season adaptation. The mid-season adaptation choice affects late-season adaptation. Finally, the early shortfall forecast determines the level of shortfall in the late-season period, thus directly affecting ex-post adaptation.

To make things concrete, consider that the adaptation choice in the early period is the share of low-water annual acreage, the adaptation choice in the mid period is fallowing land and the adaptation choice in the final period is groundwater extraction. A marginally higher shortfall early in the year likely increases a farmer's proportion of low-water annuals, and through that initial choice, will decrease the farmer's eventual fallowing decision and groundwater extraction decision. However, a lower shortfall also directly increases fallowing in the mid-season period, which in turn lowers the groundwater extraction needed in the late-season period (second line). And a higher shortfall directly increases the groundwater that a farmer will extract in the final period, all else equal.

Across the three derivatives, the same terms appear. The direct and indirect mid-season adaptation effects for example appear in both $\frac{\partial y}{\partial \hat{g}}$ and $\frac{\partial y}{\partial h_{mid}}$. Thus, we can identify the value of adaptation by rearranging coefficients in a regression of revenues on the components of information:

$$y = \beta_1 \hat{g} + \beta_2 h_{mid} + \beta_3 h_{late} + \nu \tag{5}$$

β_1 represents $\frac{\partial y}{\partial \hat{g}}$. Let the benefit of early adaptation be denoted by B_{early}, the benefit of mid-season adaptation be given by B_{mid} the benefit of late-season adaptation be given by B_{late}, and direct effect of shortfall be given by D. Then, $\beta_1 = B_{early} + B_{mid} + B_{late} + D$, $\beta_2 = B_{mid} + B_{late} + D$ and $\beta_3 = B_{late} + D$. The benefit of ex-ante adaptation is therefore identified by $\beta_1 - \beta_2$ and the benefit of mid-season adjustments is identified by $\beta_2 - \beta_3$.

It becomes apparent that in a case with ex-post adaptation, the regression of revenues on forecasts or forecast components cannot separately identify the value of ex-post adaptation and the direct effect of shortfall. In contrast, we can identify the direct effect of shortfall when profits are the dependent variable because the derivative of realized profits with respect to ex-post adaptation, $\frac{\partial \pi}{\partial a_{late}}$, equals zero by standard profit maximization. Otherwise, the other benefits of adaptation theoretically equal the same value whether I use revenues or profits.

2.3 Adaptation choices in the model

In the conceptual framework, farmers make adaptation choices to maximize profits, and $\frac{da_{late}}{dh_{late}}$, $\frac{da_{mid}}{dh_{mid}}$, etc, are critical components in driving how profits and revenues change with respect to surface water forecasts and updates. I only observe adaptation choices after $\hat{g}$, h_{mid} and h_{late} are all revealed. Let a^j refer to a specific adaptation choice, like crop fallowing. In this section, I explain what we can learn from a regression of the sum of adaptation choices after all of the surface water shortfall information has been revealed on the components of the surface water shortfall information

The first order condition on early adaptation from equation 2 showed that early adaptation depends on costs of adaptation, the substitution of adaptation decisions across periods, and the initial surface water shortfall forecast. Expectations of the later shortfall forecasts enter the implicit function through expectations on the future adaptation actions.

Consider a specific adaptation action, like crop fallowing $\tilde{a}$. The crop fallowing I observe at the end of the season is the sum of all of the crop fallowing decisions in the early, mid and late period:

$$\tilde{a} = \tilde{a}^*_{early} + \tilde{a}^*_{mid} + \tilde{a}^*_{late}$$

Taking the derivative of $\tilde{a}$ with respect to $\hat{g}$, h_{mid} or h_{late} can be interpreted as studying how a farmer's crop fallowing decisions over the season would differ if we marginally changed one component of information, holding all else equal. Like in the previous section, changing $\hat{g}$ for example would affect $\tilde{a}_{early}$, $\tilde{a}_{mid}$, and $\tilde{a}_{late}$ directly, and would also affect each adaptation choice through the substitution across periods. From the farmer's perspective in the early season, it is not the same to fallow crops early or late; fallowing early means not planting at all, while fallowing late could mean already having sunk numerous inputs into a field.

When calculating the value of adaptation in a period, the substitution across adaptation types is only important as far as it changes the marginal benefit of adaptation in a period. When parsing apart adaptation actions taken at a certain time from the ex-post totals, we cannot ignore the substitution across periods. In the regression of

$$\tilde{a} = \beta_1 \hat{g} + \beta_2 h_{mid} + \beta_3 h_{late} + \nu \tag{6}$$

And we do the same rearranging method as before, $\beta_2 - \beta_3 = (1 + \frac{d\tilde{a}^*_{late}}{d\tilde{a}^*_{mid}})\frac{d\tilde{a}^*_{mid}}{dh_{mid}}$. We do not recover the mid-season adjustments taken unless late-season adaptation is not affected by mid-season adaptation at all. In the case of fallowing, likely the opposite is true: fallowing fields in the mid-season is nearly a perfect substitute ($\frac{d\tilde{a}^*_{late}}{d\tilde{a}^*_{mid}} \sim -1$) for fallowing fields in the late-season because a field cannot be fallowed more than once. A zero coefficient could mean perfect substitution and it could mean no adaptation in the mid-season.

Instead, simply studying the effects of adaptation actions on the components of the shortfall can tell us about the sensitivity of the sum of each adaptation action to surface water shortfall revealed in different periods. The same effect throughout the year would reflect that constraints and preferences over adaptation options remain similar, while differing effects show changes in constraints and preferences. Understanding these differences will allow us to get a sense of how farm adaptation changes over a planting season even though we cannot perfectly identify the quantity of actions taken in each period. I begin by characterizing these actions over time.

3 Data

3.1 Surface Water Forecasts

I digitize all surface water allocation forecast announcements for the Central Valley Project and State Water Project, which have been published since 1967, with multiple forecast updates over multiple regions yearly (California Department of Water Resources (2024b), California Department of Water Resources (2024a), US Bureau of Reclamation (2024)). Though California farmers get information about surface water availability from a variety of sources, only these surface water allocation forecasts apply to a specific and measured source of surface water.

The CVP and SWP announce their first surface water allocation forecast in the early or mid planting season, and follow up with an average of 2.8 updates, roughly on a monthly basis, until the beginning of the dry season. I construct a panel of the newest information available to farmers at the start of the mid-planting season, late-planting season and dry season, using the surface water allocation forecasts closest to, but not beyond, February 1st, April 1st and June 1st. Table A.2 in the Appendix shows that farmers receive surface water allocation updates in these periods in most years. In some years, agencies did not publish updates in periods where the surface water allocation forecast stayed the same. The SWP typically publishes surface water allocation forecasts earlier, and finalizes its surface water allocation earlier, while in 47% of years, the CVP did not issue a first surface water allocation forecast before February 1st[10].

Overall, even though the forecasts come from different agencies, they are comparable. In appendix figure A.3, I plot binscatters comparing surface water forecasts from the State Water Project and Central Valley Project, showing that a given surface water forecast or final allocation has the same signal for both projects on average. The average surface water allocation forecast near February 1st was 36% for the SWP and 41%

[10]The CVP's reasoning is forecast reliability: "no reliable forecasts of seasonal runoff are available before February" (USBR, 1992). However, there are many spans of time where the CVP still published a forecast before February 1st.

for the CVP. Both agencies also use the same conservative forecast rule, evidenced by the higher average final surface water allocation, at 61% on average for the SWP and 60% on average for the CVP.

In years when there is no surface water allocation forecast update between February 1 and April 1, or between April 1 and June 1, I carry over the most recent surface water allocation forecast, to match the intention of the agency in retaining the previous projection. In contrast, the February 1st forecast is missing in years when the USBR's policy is to publish later forecasts. Farmers still need to make early decisions based on expected surface water availability[11].

3.2 Water districts

I use a map of 3556 water districts from California's state geoportal, augmented with alternate maps from some missing districts (California State Geoportal (2022), Public Policy Institute of California (2025), Department of Water Resources (2025c), Department of Water Resources (2025b)). I determine which districts have contracts with the surface water projects by matching names of water districts and lists of contractors using a crosswalk file from Hagerty (2022) (California Department of Water Resources (2024b), US Bureau of Reclamation (2025)). Through this process, I am able to match all 29 SWP contractors, 98 of 99 junior CVP contractors, and 81 of 89 senior CVP contractors. Figure 1 shows the geographical distribution of districts, where the colors differentiate the project contracts that each district has, and therefore the surface water forecast they receive. There is slightly more variation in the data than is present on the map because the CVP Friant, SWP alternate, CVP senior, and CVP other categories each have multiple types of contracts. For districts that have contracts with multiple projects, I scale the forecasts by the average quantity delivered from each project (U.S. Bureau of Reclamation, 2025). Overall, the project districts represent a large share of California agriculture, covering 47% of cropland California Department of Conservation, Farmland Mapping and Monitoring Program (2020).

The right panel of figure 1 shows climate regions across the state, aggregated up from level 3 ecoregions to crop planting regions, which in California roughly delineates planting seasons, groundwater basins, surface water basins, and precipitation regions (U.S. Environmental Protection Agency (2025), Pittenger (2015)). In my strongest fixed effects specification, I interact time fixed effects with these crop regions in case trends for districts in these regions differ. I overall observe 184 districts in the Central Valley, 27 in in the South and Central Coast, 5 in the Inland Desert region, and 1 in the Sierra Nevada region.

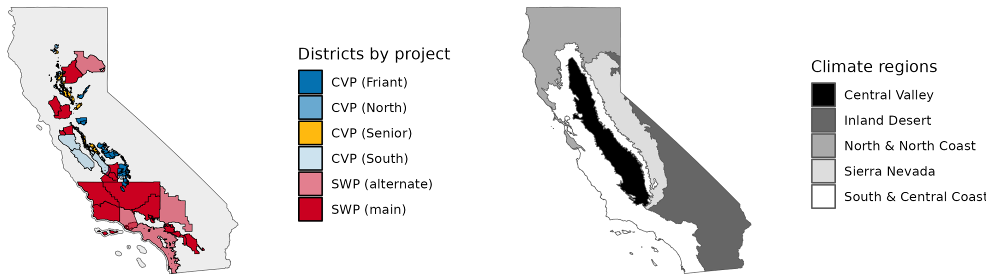
3.3 Agriculture and crop choice

For my crop-choice analysis, I use 30m x 30m crop data from USDA's cropland data layer, which runs annually back through 2007, covering years with a variety of water conditions (Boryan et al., 2011). I aggregate crop classes by planting time and watering intensity to identify whether farmers change their decision-making across either margin[12]. To make these broad crop categories, I first assign crop planting times using the USDA's usual planting and harvesting dates for US field crops (state level) and for vegetables (county level), and I supplement missing crop categories with the University of California's recommended planting

[11] "Stanislaus County farmer Daniel Bays, who grows tree and row crops in Westley, said he was already making planting decisions and preparing ground in the fall. 'To wait until March 1 to decide whether or not you're going to farm is a little late," he said. 'It could get wet for the rest of March, and you're unable to get out and prep the fields to plant.'" `https://mavensnotebook.com/2025/03/12/ag-alert-initial-cvp-water-allotment-may-not-increase-plantings/`

[12] Aggregating the data reduces misclassification (Lark et al., 2021).

Figure 1: Districts with surface water project contracts and crop regions



Note: The left panel shows the project districts in the sample. The districts shaded in blue are the 98 junior Central Valley Project contractors in the data. The different shades show areas with contracts to different canals that receive different surface water allocation forecasts. There is more detail in the data than the map, as the CVP Friant and CVP other category have multiple contract types. The yellow districts represent senior rights to the Central Valley Project, who usually have higher surface water allocation forecasts, and are curtailed in fewer years. I include these districts only in robustness checks. The districts in red have contracts to the State Water Project, which usually receive the same surface water allocation forecast across the state, with the exception of the districts shaded lighter, who have different contract terms. The right panel shows 5 major climate regions in California, aggregated up from level 3 ecoregions, which are areas that share similar climate, geology, and soils. These areas roughly delineate planting areas, groundwater basins and surface water basins in California as well, and are generally regarded as distinct agricultural areas. The districts span three of these climate regions, with the majority in the Central Valley.

times for vegetables across the four climate regions in the right panel of figure 1 (USDA, NASS (1997), USDA, NASS (2007), Pittenger (2015)). I assign watering intensity for annual crops using crop water needs equations, which is a set of water intensity coefficients and growing length from the Food and Agriculture Organization, and requires the input of planting times and local evapotranspiration, the latter of which I get from the University of California's Cooperative Extension (Brouwer and Heibloem (1986), UC Cooperative Extension and California DWR (2000)). I categorize high and low water intensity crops at the mean water use, weighted by crop area, within planting times and climate regions so that the relative water intensity represents reasonable crop choices in each region. Therefore, I have four annuals classifications depending on planting time and watering intensity: early, high-water annuals (1%), early, low-water annuals (8%), late, high-water annuals (12%), late, low-water annuals (8%). I show examples of representative crops for each climate region, planting time and category in Appendix table A.2. The overall pattern shows that annuals planted later in the year are typically more water intensive, and crop timing and water intensity depends on region. In the main specification, I omit crops that are planted both before and after the dry season because I cannot isolate which information these crops are responding to. I aggregate the remaining agricultural land classes into four other groups: perennials (29%), idled and fallowed land (27%), double-cropped and alfalfa (10%), and annuals with different planting times (5%).

3.4 Well Drilling and groundwater

I measure well drilling decisions using well completion reports publicly available from California's Department of Water Resources (California Department of Water Resources, 2024c). Well drilling contractors have been required to report well completion, modification and removal within 60 days of the action since 1967, giving me the universe of completed wells (Department of Water Resources, 1981). The data include the date completed, location (to a 1 mile section), purpose (agriculture, monitoring, etc) and action taken (completion, removal, etc) for each well. My main variable of interest is the sum of agricultural wells completed in a district between February and August, which should capture most well drilling decisions responding to surface water supply forecasts and realizations after accounting for the drilling delay[13]. In total, I observe 36,663 agricultural wells drilled in the districts that I study from 1967-2022. By the end of the sample there is about 1 agricultural well for every 185 acres of agricultural land in these districts.

For depth to the groundwater table, I take an unbalanced panel of over 5 million monitoring well measurements from California's Department of Water Resources, and I interpolate a seasonal groundwater depth raster at a 1 kilometer resolution, using the inverse-distance-weighted depth to the groundwater table for well measurements within 5 kilometers (California Department of Water Resources, 2025). The interpolation allows me to get more frequent and higher spatial resolution on groundwater depth observations, since few monitoring wells exist throughout my long panel. The procedure should also be reasonable given California's relatively homogeneous aquifers.

3.5 Other variables: farm profits, weather, streamflow forecasts

For the maximized values needed in this analysis, farm revenues, costs, and profits, I use the BEA's county-level farm income and expenses dataset, which ran from 1969 to 2024. I measure crop revenues with cash receipts from crops, and crop inputs using the sum of all production expenses, excluding livestock purchased and feed purchased. I calculate profits by subtracting the costs from the revenues. For streamflow forecasts, I use the Department of Water Resources's forecasts for dry-season runoff as a percent of the average, which it began publishing in its snow survey in 1955 (Department of Water Resources, 2024). I digitize these runoff forecasts from 1965-2022, assigning them to districts based on which subbasin the centroid of the district intersects with, since streamflow relates to stream diversion rights. Finally, temperature and precipitation data comes from NOAA's nClimGrid (Durre et al., 2022).

4 Actions taken in response to surface water supply shocks

4.1 Methods

In this section, I study which adaptation actions farmers take in response to surface water scarcity, and whether they take different actions in response to information revealed at different points in the year, which will allow us to understand how sequential decision-making changes adaptation behavior. The government announces the final amount of project surface water available to water districts around June. However, the final surface water allocation is revealed throughout the growing season, first with a baseline surface water allocation forecast in January or earlier, and then with updates irregularly throughout the season. Therefore, the contractual share of project surface water delivered is composed of several parts, which I simplify into three parts for the empirical analysis:

[13] 82% of wells include a purpose.

$$\underbrace{s}_{\text{June SW allocation shortfall}} = \underbrace{\hat{s}}_{\text{Jan. SW forecast shortfall}} + \underbrace{\varepsilon^{\text{mid}}}_{\text{March 1st forecast update}} + \underbrace{\varepsilon^{\text{late}}}_{\text{June 1st forecast update}} \tag{7}$$

Where the shortfall is defined as the amount of a contract not fullfilled, or 100% - the surface water allocation forecast percentage, and the updates are defined as the previous surface water forecast shortfall minus the current surface water forecast shortfall. Both ε components represent how the surface water forecast has changed from the previous announcement between the time of the previous announcement and either March 1st or June 1st. I could regress the levels of adaptation decisions on s to learn the sensitivity of different kinds of adaptation to surface water scarcity. Instead, I regress the levels of adaptation decisions on the three components to learn about why different decisions are taken. As long as I have variation in how information updates across districts within years, then I can identify how each component results in the level of an adaptation action.

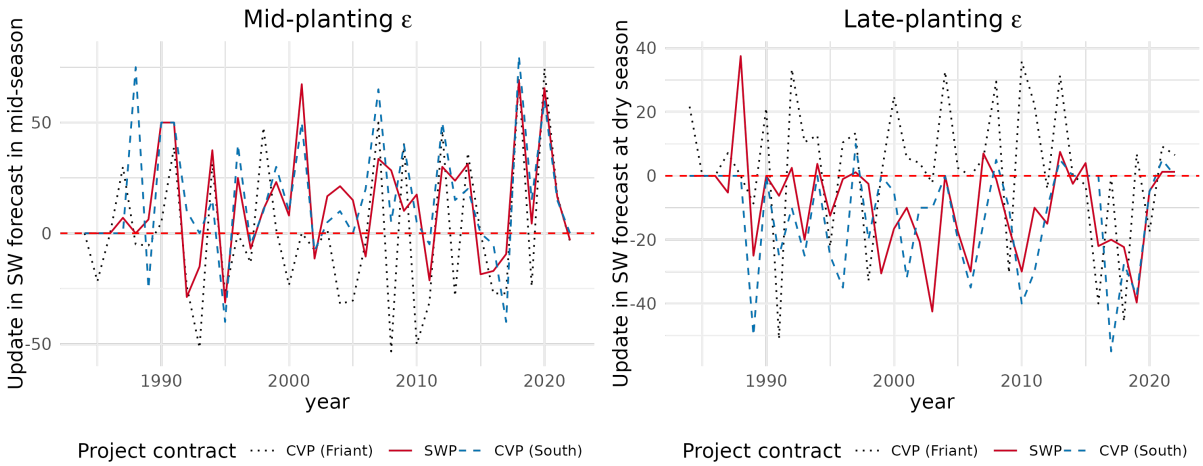
I estimate the following econometric model:

$$A_{dt} = \exp(\beta_1 \hat{s}_{dt-1} + \beta_2 \varepsilon_{dt}^{\text{mid}} + \beta_3 \varepsilon_{dt}^{\text{late}} + X_{dt} + \gamma_d + \gamma_{rt} + \nu_{dt}) \tag{8}$$

A_{dt} is the cumulative level of action A observed in the dry season, after all surface water information has been revealed, in district d in year t. I study four actions. The first is well drilling, so that A_{dt} is the cumulative number of wells drilled in district d until the end of the dry season (January - August). Second, I study groundwater extracted, which is proxied by the change in the depth to the groundwater table. A_{it} is the level depth to the groundwater table in feet at the end of the dry season (August), so that the βs can be interpreted as changes in depth. Third, I consider land fallowing, so that A_{dt} is the number of idled acres in a district, as observed during the peak harvest time. In the final set of regressions, A_{dt} is the number of acres at peak harvest in other annual crop groups, grouped by water intensity. Since A_{dt} is always bounded below by zero, where zeros usually reflect a meaningful choice, I estimate the model using PPML (Silva and Tenreyro, 2006). Poisson regressions naturally represent the aggregation of individual binary choices (Cameron and Trivedi, 2013). Since Poisson regressions are not typical in the crop-choice literature, I check the robustness of my Poisson results using a simple fractional logit crop choice model, following Kurukulasuriya and Mendelsohn (2008)

There are three coefficients of interest, β_1, β_2 and β_3, each a component of information from (7). β_2 for example equals $\frac{d\log(A_{dt})}{d\varepsilon_{dt}}$, and so is approximately the percent change in an adaptation action with a 1 point increase in the shortfall update. Because of the definition of this variable, a 1 point increase in the shortfall update is a decrease in the announced surface water allocation by 1 percentage point, for example going from 80% of the contract to 79% of the contract delivered. The intuition from the conceptual framework can guide our interpretation of the coefficients. β_1 is the sum of the changes in the cumulative adaptation observed due to ex-ante choices and expected ex-post choices, where ex-post refers to the periods of time after the baseline surface water forecast where new information is revealed. β_2 captures the adjustments made due to the changes in information between the baseline forecast and the middle of the planting season, which includes adaptation expected to be taken later in the season. Finally, β_3 includes ex-post adjustments due to the change in surface water availability since the middle of the season. The direct effect of surface water availability comes from $\beta_1 + \beta_2 + \beta_3$.

Figure 2: Variation in the data: ε^{mid} and $\varepsilon^{\text{late}}$ for three major project contracts



Note: The plot shows the levels of ε^{mid} (the left plot) and $\varepsilon^{\text{late}}$ (the right plot) for districts with the standard State Water Project contract, the south-of-delta Central Valley Project contract, and the Friant Canal Central Valley Project. The line falling above zero means that the current surface water allocation forecast is lower than the previous information, or that the shortfall increased. The plot shows that there is often a lot of correlation between the forecasts, yet there are differences in the magnitude of ε, even within the same project.

I identify the response of adaptation actions to surface water scarcity information revealed in different times of the year using the variation in forecast updates across regions. Figure 2 shows an example of the variation using forecasts for three different contracts present in the data. I plot ε^{mid} (the left plot) and $\varepsilon^{\text{late}}$ (the right plot) for districts with the standard State Water Project contract, the south-of-delta Central Valley Project contract, and the Central Valley Project contract to water on the Friant Canal. The line falling above zero means that the current surface water allocation forecast is lower than the last, or that the shortfall is positive. The news across project contracts is correlated, showing that districts get hit with high and low surface water years at the same time. For mid-year forecast updates, the correlation between the lines range from 0.57 and 0.71, and for late forecast updates the correlation ranges from 0.18 to 0.52. Despite the high correlation, there remains a considerable amount of variation in how districts' surface water allocations evolve throughout the year.

X_{dt} is a set of district-year specific controls that control for endogeneity between information and the adaptation choice. There are four main sources of endogeneity. The first is peer effects: one district's response to surface water availability sometimes affects other districts' responses. Peer effects is especially a problem for well drilling which has a fixed number of contractors in the short-term, so that a higher demand for wells may increase the price, and certainly increases the wait time. Therefore, I include neighboring districts' well drilling decisions, and neighboring districts' groundwater extraction as a control in X for the respective regressions. The second source of endogeneity comes from local weather and alternative water sources, which are both correlated with surface water allocation forecasts and likely with adaptation decisions. So, for all three choices I include controls for temperature, precipitation, and streamflow forecasts and realizations, and for lagged depth to the groundwater table when it is not the dependent variable. The third source of endogeneity is that there is some autocorrelation in the forecasts which might correlate with past capital-intensive decisions like perennial planting and well drilling, which affect current decisions through the diminishing returns to wells, and switching costs (Scott, 2014). I account for this source of endogeneity by including the lagged perennial acreage in districts, and the lagged cumulative wells in districts in the crop and well choice regressions respectively.

The final, and most complicated, source of endogeneity is the alternative adaptation decisions. Because the adaptation decisions are substitutes, each A_{dt} modelled by equation (8) one of several simultaneous equations. Since I have a non-linear model of adaptation decisions, I control for the endogeneity from these alternative decisions using control functions (Imbens and Newey, 2009). Intuitively, the residual of estimated adaptation decisions conditional on exogenous variables still includes the effect of the other adaptation choices on the decision. Including those residuals in my regression control for the endogeneity. Although I will not control for all alternate decisions, including control functions for the main adaptation substitutes will allow us to see how important the bias from this source of endogeneity is. The requirements for excluded instruments in control functions follows the intuition of standard instrumental variables. I use instruments that capture surprising changes in adaptation-specific input prices, which only affect a substitute choice only through the level of the other choice. For the well drilling control function, I use the interaction of steel pipe prices and the depth to the groundwater table, as well as the interaction of the number of well drilling contractors and drilling machinery prices. For the crop idling control functions I use the interaction of prime farmland and fertilizer prices. For groundwater extraction, I use the interaction of electricity prices and regulation on extraction.

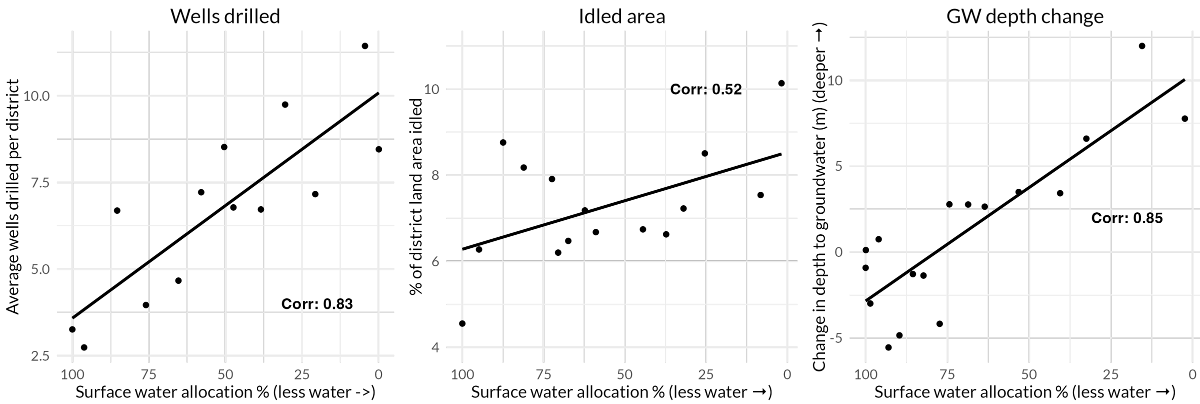
Finally, ν_{dt} is the error term. In my main specifications, I cluster standard errors at the district level because surface water forecasts apply to specific districts. For most forecasts, the treatment (weather) is not applied to a specific location, so spatial correlation robust are usually more applicable (Shrader, 2023). In robustness checks, I employ a combination of Conley (1999) and Newey and West (1987) standard errors with various distance cutoffs and time lags to show that my results are robust to multiple standard error specifications.

4.2 Results

The first result is that farmers respond to water scarcity using both water intensifying and water conserving adaptation practices. I motivate this fact using a simple raw-data binscatter of wells drilled, idled land and the change in depth to the groundwater table on the final surface water allocation percent. The raw data relationships are displayed in figure 3. Worse surface water allocations correlate strongly with higher uptake of each of the farm adaptation options. Although the raw data plots cannot confirm whether farmers respond specifically to the allocation forecasts, they give strong evidence for farmers adapting to surface water supply changes in general. Because groundwater extraction is unregulated and has a higher social cost than water conservation, it would be socially beneficial for some portion of adaptation through groundwater use to be substituted with adaptation through water conservation. The main empirical specification explores why farmers take one decision over another in the context of information timing.

In figure 4, I plot the main β coefficients of the PPML regressions, which show how each adaptation action responds to the components of the surface water shortfall revealed at different times throughout the season. All of the coefficients and standard errors have been transformed to show a percent change in the action with a one percentage point decrease in the surface water allocation forecast. Broadly, the patterns are the same as the raw data plots: an increase in surface water shortfall causes farmers to take both water conserving and water intensifying adaptive actions.

Figure 3: Raw data binscatter: Adaptation actions on surface water allocation forecasts



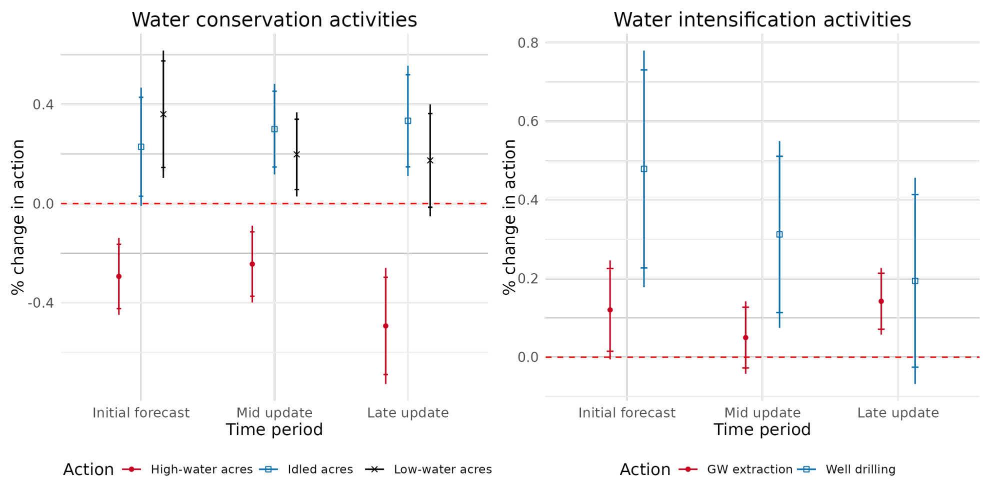
Note: On all plots, the x axes are flipped so that a stronger shock to surface water supply (a lower surface water allocation) corresponds to a higher adaptive action. The left plot shows the average number of wells drilled, the middle plot shows the average percent idled area, and the right plot shows the change in a district's average depth to the groundwater table from the prior year, all binned by the surface water allocation forecast. Every plot shows a strong relationship between low surface water allocations and taking adaptive action.

The left plot shows changes in crop choice, which is usually a water conserving adaptation choice, because farmers can tailor their acreage to the amount of surface water that they expect. The blue squares and black x's are water saving crop choices, through idling and low-water acreage respectively. Low-water acres are typically planted early in the year, when lower temperatures drastically reduce crop water requirements. Coefficients on these choices are positive and significant, showing that farmers fallow crops and plant lower-water-intensity annuals in low surface water years. On the other hand, high-water acreage is represented by the red dots on the plot. High water acreage decreases in response to surface water allocation shortfall. The multinomial logit crop choice results in appendix table B.3 shows the same patterns.

The different coefficients show how the crop responses change over the growing season. Overall, most coefficients remain statistically significant throughout the growing season, showing that farmers continue to adapt with crop choice as they receive new information. The patterns in the magnitude of the coefficients suggest that I am capturing a true effect. By the late surface water allocation update, farmers respond less by increasing low water acres, since there are few low-water options left. The idling response remains strong, and the decrease in high water crops becomes even larger than previous. Since high-water crops are often planted in April and May (e.g. cotton and rice), there is still flexibility to decrease acreage in these crops in response to late surface water shortfall news. These coefficients translate to roughly 8.4, 11, and 12.2 new idled acres in each period for the average district, 1.5, 0.75, and 0.65 new low-water annuals for the average district and 1.6, 1.32 and 2.6 fewer high-water annuals for the average district for a marginal change in the surface water shortfall.

The right plot shows the response of groundwater intensifying actions to surface water allocation shortfall, which are the percent changed in wells drilled (blue boxes) and the percent increase in the depth to the groundwater table, in feet (red dots) which I use as a proxy for groundwater extraction. Like the raw data plots suggested, farmers increase groundwater intensifying adaptation in response to surface water allocation shortfall. The change in depth to the groundwater table is especially high and statistically significant in response to the latest surface water information announced. In contrast, well drilling decisions clearly

Figure 4: Coefficient estimates on percent changes in actions with a 1 percentage-point change in surface water information



Note: This figure shows the coefficient responses to the full specification of equation (8), including controls for alternate water sources, neighbors' choices, and past capital-intensive choices, control functions for other adaptation choices, and district and climate region-year fixed effects. Each point is one PPML regression, with the dependent variable listed in the legend. The points show the coefficient estimates of a 1 point change in the surface water allocation or forecast available at each of the time periods. The 90 and 95 percent confidence intervals are also plotted, clustered at the district level.

decrease as the dry season approaches. Even though well drilling is a long-term investment, the regressions show that farmers respond to short-term surface water availability information by drilling.

Both of these patterns make sense in light of the constraints of adaptation in the setting. Groundwater extraction on existing wells can occur at any time, and therefore is the most flexible of the adaptation options I consider. It is constrained only by the capacity of the well. For well drilling, there is a yearly tension between the option value of delaying drilling until the final surface water shortfall is realized, which will give the farmer more information about long-term surface water availability, and the short-term gain of being able to use groundwater a year early if the surface water shortfall is especially high. Farmers would be incentivized to make drilling decisions early in the latter case because of the delay between the drilling decision and completion of the well, caused by permitting and demand queues. The pattern of drilling that I find shows that farmers tend to make drilling decisions early to ensure that they can use their well in the current dry season. The estimated coefficients suggest that depth to the groundwater table increases by 0.1, 0.03 and 0.14 feet for the average district for every marginal increase in the surface water allocation shortfall over the three periods of the year, and that approximately 1 out of every 62, 100 and 150 districts drill a new agricultural well.

The adaptation response results are robust to omission of controls, and different fixed effects. The main coefficient estimates and these alternate specifications can be found in appendix table B.3. The results are robust to a variety of other specifications as well. Appendix table B.3 shows that I get the same response pattern if I model crop choice using multinomial logit rather than Poisson. Table B.3 shows the results are robust to different versions of the dependent variable, including by changing the specific time of observation of the adaptation action (e.g. by using wells drilled all year), and different winsorization levels. A modest level of winsorization of wells drilled is required for statistical significance. The results are also robust to project-type by year fixed effects, which compare within the categories of junior CVP, senior CVP, and SWP contracts, which makes sure that the results are not driven by bad comparisons across projects. The final robustness check, figure B.5 shows that the results are robust to using a combination of Conley and Newey-West standard errors across a variety of cutoffs.

4.3 Heterogeneity by news direction and district characteristics

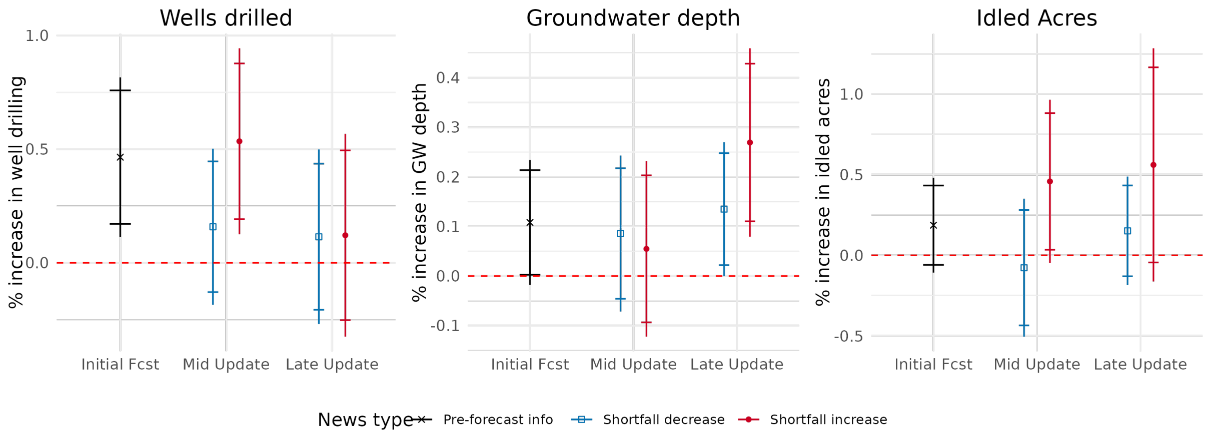
I have established that farmers take both water conserving and groundwater intensifying adaptation actions in response to increases in forecasted and actual surface water allocation shortfall. However, if the effects are really linear, then changes in adaptation should balance out over time and space as sometimes districts take more adaptive actions than usual, and sometimes they take less. In the case of linear adaptation responses, there are still social costs of groundwater extraction if groundwater tends to be depleted heterogeneously across space; there is also a time-value of groundwater. Yet, the social costs will be substantially higher if farmers respond to bad news by extracting groundwater more than they respond to good news by decreasing groundwater use.

I examine whether farmers have different adaptation responses to good and bad news about surface water shortfall by interacting the surface water allocation updates (ε) in equation (8) by an indicator variable which equals one when surface water shortfall increased (bad news, $\varepsilon \geq 0$) and zero when it decreased (good news, $\varepsilon < 0$). In figure 5 I plot the differential adaptation responses in cases of increasing and decreasing shortfall. The blue boxes show the marginal adaptation response for a 1 percentage point increase in the shortfall when the shortfall update was negative, and thus shows the effect of marginally worse good news. The red dots show the marginal adaptation response when the shortfall update was positive, and thus is marginally worse bad news. The overall trend in the plot shows that in periods that had significant effects in figure 4, the adaptation response tends to be larger and more statistically significant when the shortfall update is positive than when it is negative. Both the water conserving and groundwater intensifying actions display the same trend. Farmers have strong adaptation responses to bad surface water news, and potentially very little response to good surface water news.

The most important insight from the heterogeneous response analysis is that positive surface water shortfall updates increase adaptation actions without commensurate decreases in adaptation in years where the shortfall decreases. If adaptation responses increase groundwater use in response to a bad surface water shortfall shock, then over time groundwater use is higher than it would have been absent surface water shortfall shocks, potentially leading to a social cost of adaptation.

In order to understand the characteristics of farm adaptation, I conduct a few other heterogeneity analyses, which I include in the appendix. Well drilling likely changes over time since it is not a recurring annual choice like annual cropping and groundwater extraction. Once a well is drilled, a farmer no longer needs to make a well drilling decision. So, at the district level, we should view a diminishing return to wells. I interact the surface water allocation forecasts in the main specification with the log of the lagged number of wells in a district, and plot the marginal response to the final surface water allocation in appendix figure B.4. The plot matches the economic intuition that districts' responses to information is significantly higher than the average response when a district's number of wells is low. As a district's number of wells increases, the district stops responding to low surface water allocations with well drilling. In an alternate heterogeneity analysis, I make sure that I am convincingly capturing the effect of the surface water allocation forecast by interacting the estimated percent of surface water in the district that comes from surface water projects with

Figure 5: Heterogeneous adaptation responses by increasing and decreasing surface water shortfall



Note: These three plots show the coefficients on three adaptation responses for each time period, where the updates are separated into 'good' and 'bad' news if the surface water shortfall decreased ($\varepsilon < 0$, shown by blue boxes) or increased ($\varepsilon \geq 0$, shown in red dots) respectively. I estimate these effects by interacting the surface water allocation updates (ε) in equation (8) by an indicator. The points show the coefficient estimates of a 1 point change in the surface water allocation or forecast available at each of the time periods. The 90 and 95 percent confidence intervals are also plotted, clustered at the district level. Overall, the general trend in the results show that the adaptation response is generally larger in the case of bad news. I also find insignificant results in the same periods where I found no significant response in figure 4.

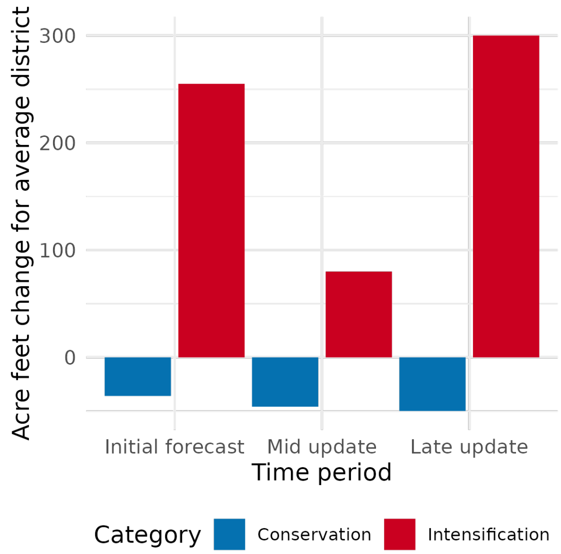
the surface water allocation forecasts and updates. As expected, a higher percent of project water results in a stronger well drilling response to the surface water allocation forecast changes. Finally, I also interact the percent of a district's land in perennials with the surface water allocation forecasts, and I find that districts respond with well drilling when they have more land in perennials. The final result shows some of the complementarities in choices in agriculture.

4.4 Change in water use through adaptation

Not only do farmers use water-intensifying and water conserving strategies to adapt, but they tend to adapt when surface water shortfall updates are positive, and not when they are negative, suggesting there could be a long-run net positive increase in groundwater withdrawals from adaptation. To conclude this section, I approximate the magnitude of changes in water use from both types of actions. I assume that low-water acreage uses 2 acre feet per year, high-water acreage uses 4 acre feet per year, and fallowed acreage uses 0. I do not calculate substitution patterns in this paper, so I make the following assumptions: low-water acreage is substituted from high-water acreage, and the rest of the high-water acreage change becomes fallowed land. Since I observe more land fallowing than other changes in acres (I do not include pasture land, or perennial land in this crop choice analysis), I assume that other fallowed land saves 3 acre feet per year on average. For change in groundwater extraction, I assume an equal groundwater level change over all planted acres in the district. I multiply the acres by the groundwater level change by the estimated porosity of the aquifer, which is the measure of groundwater storage per volume of earth (Ojha et al., 2018). The change in groundwater use from new wells is complicated. I omit the estimate in the current analysis, returning to it after section 7 where I study dynamic consequences of well drilling.

Figure 6 shows the results of the back-of-the-envelope calculation for every period. In response to a

Figure 6: Change in water used after a 1 percentage point change in surface water shortfall



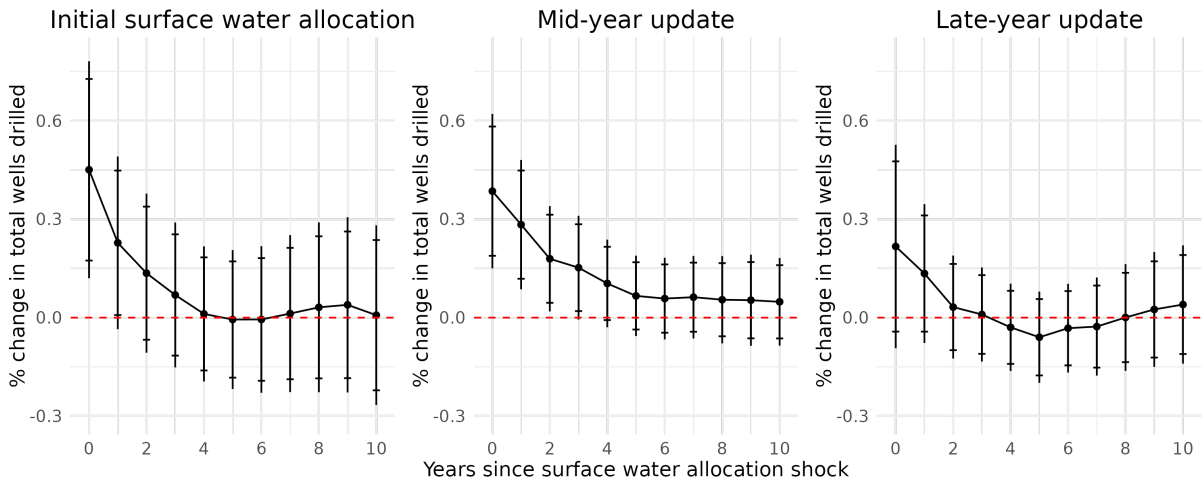
Note: This figure shows the back-of-the envelope calculations for decreases in water use from water conservation from changing crop choice, and groundwater intensification from groundwater extraction, using the estimates in figure 4. I omit any change in groundwater from new wells. The y-axis shows the acre feet change for every district from a marginal increase in surface water shortfall resulting from these changing adaptation practices.

1 percentage point increase in the surface water allocation shortfall in every period, the average district increases groundwater use by about 635 acre feet, and decreases water use by about 130 acre feet. The main takeaway is that even without including the effects of new groundwater wells, farmers increase groundwater use up to 7 times more than they decrease surface water use in certain periods of the year, and groundwater use is always at least twice as strong as the water conservation effect. Because groundwater extraction is socially costly, this result raises the question about how socially beneficial adaptation to water scarcity is. To study the net benefit of adaptation, I estimate the aggregate private value of adaptation in the next section. Afterward, I explore the less straightforward, but potentially important dynamic social costs from the well drilling decision.

5 Adaptation in the long-run: effects of well drilling

In section 4 I found that farmers in California respond to surface water scarcity primarily from increasing groundwater extraction, even while ignoring the effect of well drilling. In this section, I turn to explore the long-run effects of well drilling more carefully. First, I seek to explain why farmers would respond to short-run water shortfall shocks with making a capital intensive investment. I use local projections to find the persistence of the effect of a one-time surface water shortfall shock on the total stock of wells in a district. The persistence will show whether farmers drill a well early, or whether they would never have drilled a well at all; it also gives the length of time that external costs persist after a surface water shortfall shock. After showing why farmers drill wells, I study how their actions change after drilling. First, I study how the size of the stock of wells in a district affects the sensitivity of actions to surface water scarcity, which gives us an

Figure 7: Dynamic well drilling response to surface water allocation shocks



Note: This plot shows the cumulative dynamic well drilling response to a surface water allocation shock in year zero, using local projections. A coefficent of zero shows that the number of wells drilled is the same as the expected trend.

idea about the substitution between short and long term adaptation strategies. Then, I study how drilling a well affects the groundwater use in a normal year for farmers likely to drill a well in the near future. Finally, I study how exogenous new wells affect farmers' crop choices in the years after drilling.

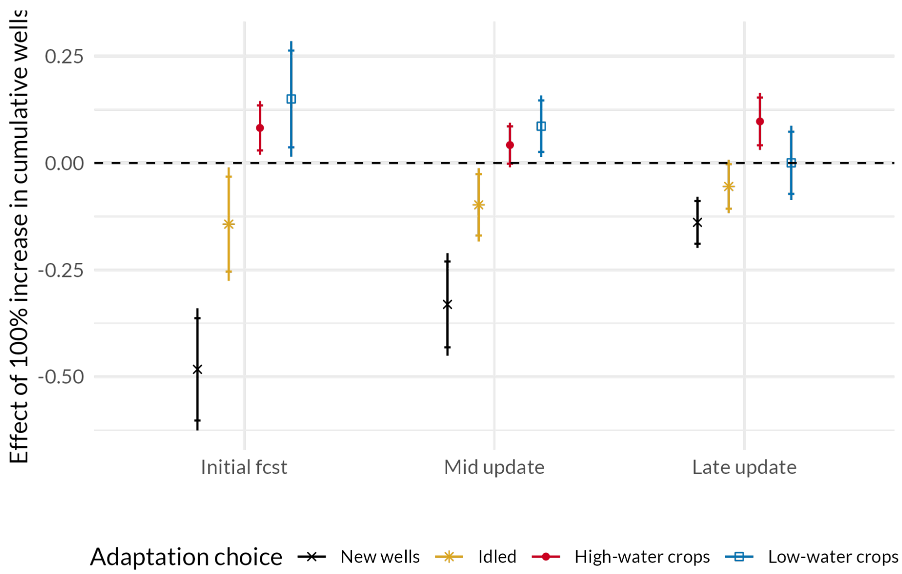
5.1 Dynamics of well drilling: most wells are temporarily excess, some may be permanent

I study when wells would have been drilled had it not been for the surface water allocation shock using local projections (Jordà, 2005). Local projections will show the impulse response of a surface water shortfall shock in year t on the path of cumulative new wells in a water district from immediately before the shock occurred $(t-1)$ until the year $t+h$. The main assumption required is that the surface water shortfall shock in t is not affected by the number of wells drilled in t, the same assumption from the previous analysis (Jordà, 2023). The estimating equation is similar to equation (8), where the major difference is that the dependent variable is the sum of wells drilled in a district from year $t-1$ to year $t+h$. I also include two lags of the number of wells drilled and the previous shocks, which is standard in local projections for ensuring the exogeneity of the shock and correcting for bias in the standard errors (Montiel Olea and Plagborg-Møller, 2021). The results are robust to different numbers of lags. I then run $h = 10$ separate regressions, and plot the path of coefficients in figure 7.

The response to well drilling in the year when a surface water shortfall shock occurs is virtually the same as those shown in section 4[14]. Then, all of the plots show the same trend: the effect of a surface water shortfall shock on the cumulative number of wells in a district decreases monotonically after the shock occurs, until the increase becomes insignificant. About half of the wells drilled in response to initial surface water allocation information are shifted forward only between 1 and 2 years. After four years, there is a precise zero effect on the number of additional wells in a district. For the mid-year surface water shortfall update,

[14] The coefficient estimates differ from the main specification because of the local projections controls.

Figure 8: How the stock of wells affects the sensitivity to taking action in each period



Note: This plot shows the results of the main specification in equation (8), where the main regression coefficients are interacted by the logged lag cumulative wells in a water district. I plot the coefficients of the interaction.

wells would have been drilled further in the future. The increase in wells remains marginally statistically significant four years into the future, where afterward the trend becomes insignificant, but levels off above zero. The average point estimate six years and beyond the surface water allocation shock and beyond is .053, which is 14% of the magnitude of the coefficient in the first year. So, about 14% of the initial increase in wells might be permanent. Permanent effects can come from a shift in individual farmers' future beliefs about the value of wells, or due to the proportional shift upward in everybody's well value which moves the entire path of well drilling forward in time.

Despite the insignificance of a long-term trend, there is still a real social cost to the shifting forward of wells in time. Groundwater is likely used earlier, leaving less time to regulate the aquifer, and shifting externalities forward in time.

5.2 Well drilling affects short-term adaptation decisions

Well drilling gives farmers access to groundwater, which decreases the price of water in years where surface water is scarce, since the price of surface water tends to be much more variable. Therefore, the private value of conserving water should decrease after a farmer drills a well.

I perform a simple test to see whether this intuition reflects in the data. I take the original estimating equation (8) and interact the components of information by the log of the lagged cumulative wells in a water district, a pre-determined variable. The interaction term will show how much less sensitive districts get as the number of wells increases by approximately one percent. The interaction effect of lagged cumulative wells and surface water scarcity components is shown in figure 8.

In comparison with the baseline results, the coefficients on the interaction term reverse the effects of surface water scarcity on nearly every adaptation decision. Idled acreage decreases as the stock of wells increases, and the switch to high-water crops increases. Low-water crops also increase, the sole exception to the pattern; however, the increase in low water crops might be substitution from idling rather than high-water crops. The largest change comes from responses to earlier information, suggesting that well drilling decreases the value of ex-ante adaptation.

5.3 Groundwater use increases after well drilling

I next estimate how much groundwater use increases after wells are drilled. It is not obvious whether farmers immediately increase groundwater use, nor if they increase groundwater use in normal surface water years. Farmers might use groundwater in every year if the price of surface water in districts is set lower than the marginal product of water in every year.

Groundwater extraction and well drilling are simultaneously determined by surface water scarcity, weather, prior wells drilled, and a host of other variables. I use well supply shifters as instrumental variables to capture well drilling decisions unaffected by current water conditions. I form the instrument by interacting the one-year lagged number of well contractors serving the district by well input prices. For my main analysis, I use yearly steel piping prices from FRED, since large diameter steel piping is common for well casing in large agricultural wells. I check for robustness to other well inputs including oil drilling machinery prices (a proxy for water well drilling machinery) and plastic piping prices (PVC casing is common for smaller agricultural wells). More past well contractors increase competition for drilling and lowers prices. Well contractors cannot enter the market immediately because of certifications and machinery investments required. I control for any demand-driven changes in well contractors by using the current number of contractors as a control in the regression. Otherwise, I use the same controls as explained for equation (8) where I estimated the change in the depth to the groundwater table with respect to surface water scarcity information.

The instrument I propose slightly changes the value of wells through the cost of wells. The instrument will affect farmers who already have a well value near the threshold of profitability. Since the local projections analysis suggested that a minor shift in the well value only accelerates drilling for these farmers at the threshold by a few years, we can expect that the local average treatment effect shows how farmers with moderate well values (since they had not drilled already) who would have drilled a few years in the future increase their groundwater use in a normal year (since the instrument does not correlate with water availability) after drilling a well. Overall, although the instrument identifies a very specific local average treatment effect, it is relevant: I am capturing how groundwater use changes on average for the farmers likeliest to drill next.

Table 2 shows the first stage table for my main instrument, where each column adds more controls and fixed effects. Given a plastic pipe price in year t, the interaction tells us whether the price affects regions with more or fewer contractors. The positive coefficient in the table suggests that areas with more contractors drill more wells in years with high plastic pipe prices. This makes intuitive sense because contractors must remain competitive even as prices go up. Overall, the instrument is strongly predictive and has a moderate F-statistic of around 30. The other instrument, the lag of the log of contractors shows the intuitive result that more wells are drilled in areas that have more contractors. The coefficient on the interaction remains very similar when we include the control for current contractors in column 3, though given current contractors, having more contractors in the previous period means that fewer wells are drilled, suggesting that the current contractors variable does capture demand responses.

I show the results of the OLS and IV regressions of the percent change in the groundwater table on the

Table 2: First stage: wells drilled in response to well prices

	(1)	(2)	(3)
Lag log(contractors) × plastic pipe price	0.002^{***}	0.002^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)
Lag log(contractors)	0.139	0.163^{*}	-0.636^{**}
	(0.087)	(0.088)	(0.263)
Log(contractors)			0.839^{***}
			(0.293)
Controls	no	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	no
F-stat	29.424	29.286	29.283
Num. obs.	4576	4495	4363
Adj. R^2 (full model)	0.749	0.750	0.743

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: These plots show regressions of the logged number of agricultural wells drilled in a district on the interaction of the previous year's logged number of contractors and the current plastic pipe price. Each column adds stronger fixed effects or controls. (1) has only district and year fixed effects, (2) adds all of the controls in the previous specifications and, (3) adds the current logged contractors, the control needed to make the instrument valid. The first two variables listed make up my instrument, which jointly have an F-statistic of nearly 30.

percent change in wells in table 3. The across specifications, the results consistently show that new wells correlate with increased depth to the groundwater table. It is not clear whether the bias in OLS would be upward or downward. Over time, districts drill fewer wells and extract more groundwater on their stock of wells (although I control for the well stock). At the same time, wells are drilled in low surface water years, when extraction is particularly high. Column 4 shows the preferred instrumental variables specification with all controls included. Interestingly, the local average treatment effect is much higher than the OLS result. I find that for every 1% increase in wells in a water district, the depth to the groundwater table increases by 0.16%. Either OLS is very biased, or the farmers most likely to drill next are likely to use more groundwater in an average year.

The estimate for the change in groundwater use is high but reasonable. A 1% change in new wells is difficult to quantify because wells are a discrete object. At the average rate of well drilling, a 1% increase is about 1 new well for every 16 districts. If we assume that a district with a new well gets 16 times the average effect, and the other 15 get 0 effect, the district with a new well faces a 2.08 foot drop in their water table on average. The USGS estimate for the change in depth to the groundwater table for a large agricultural well after 1 year of pumping is about 5 feet within a quarter mile of the well, and 2 feet at one mile from the well (Kunkel, 1960).

5.4 Post-well drilling farm decisions: farms plant more water-intensive crops

I finish off my study of the effect of drilling wells on other adaptation decisions by exploring whether drilling affects later cropping decisions. Drilling a well gives farmers permanent access to a surface water substitute with a stable marginal price, which increases the value of higher-water acreage and decreases risk of crop losses, especially for perennials. I explore the dynamic path of crop acreage using local projections.

Table 3: Percent change in groundwater depth with 1% change in wells

	OLS	IV	OLS	IV
log(New agricultural wells)	0.038^{**}	0.239	0.027^{**}	0.161^{*}
	(0.016)	(0.191)	(0.010)	(0.091)
Controls	no	no	yes	yes
District FEs	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes
First stage F-stat	NA	27	NA	32
Num. obs.	4979	4979	4733	4733
Adj. R^2 (full model)	0.817	0.804	0.886	0.881

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: The table shows the regression of the log of the depth to the groundwater table in August on the log of the new wells drilled in the district prior to August. The first two columns only include district and year fixed effects, while the final column includes controls for alternate water sources, crop choice (using a control function), and previous drilling decisions. The instrumental variable used is the lag of the number of well drilling contractors in the region, interacted with well drilling machinery prices. To make the instrument valid, I also include the current number of well drillers as a control, since drilling contractors are influenced by demand, though there are significant barriers to entry for becoming a contractor. The table includes the F-statistic of the first stage, which shows that the instruments are strong.

Like with groundwater extraction, crop choices and well drilling are simultaneous. The decision to plant perennials increases the value of a well, and drilling a well increases the value of perennials. Therefore, like in the previous analysis I instrument for exogenous new wells using the same well drilling cost shifters, which affects the well supply curve without affecting crop choice except through the wells choice.

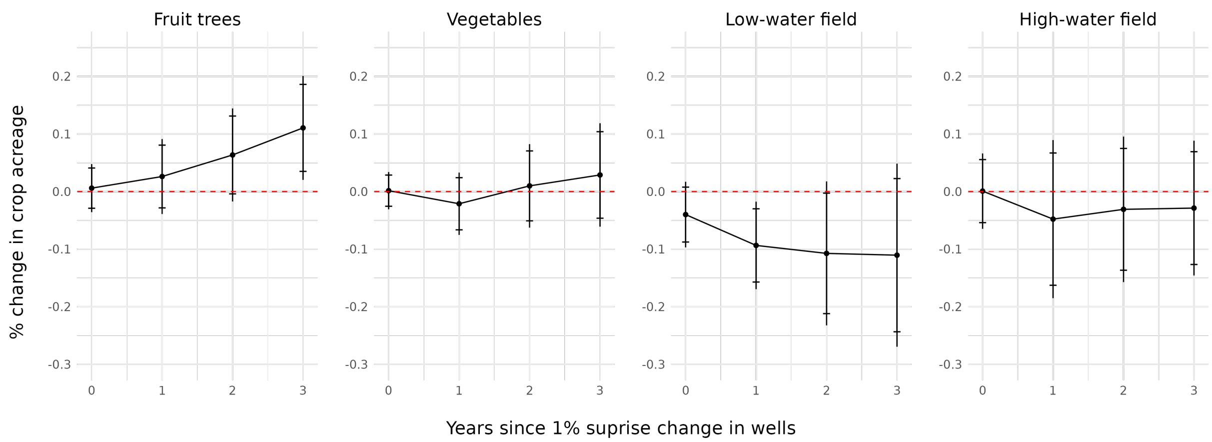
Local projections can be combined with instrumental variables analysis straightforwardly, by performing two-stage least squares in each of the h local projections regressions (LP-IV) (Jordà et al., 2015). In addition to the standard instrumental variables assumptions, IV with local projections requires a third assumption of lead-lag exogeneity, where the instrumental variable is only correlated with the contemporaneous shock of interest and not with past or future shocks (Stock and Watson, 2018). Fortunately, the standard local projections controls (past well drilling) makes the instrument valid. A drawback of LP-IV is that I cannot use PPML. The best I can do is a transformation of well drilling either using inverse hyperbolic sine or the logarithm of wells, plus one. Neither is ideal, though I show that the results across both specifications is consistent.

Local projections leads to bias in small panels, so the Cropland Data Layer is not ideal. Since I am not directly studying surface water forecasts in this section, I am not bound to district-level data. Therefore, I perform the main analysis using a county-level dataset of harvested cropland available from 1980 to 2022 from California's Agricultural Commissioner (CA Agricultural Commissioner, National Agricultural Statistics Service, 2025). I aggregate all variables to the county level. I use the same weather and streamflow controls as previously to be consistent with the previous specifications and to increase precision. I cluster standard errors at the district level since my well drilling contractors instrumental variable is assigned to districts.

For the dynamic path of groundwater extraction, I estimate the local projections with standard local projections rather than LP-IV. The value-added of groundwater jointly determines well drilling choices and groundwater extraction choices. However, local projections directly controls for well demand through lags of previous well drilling choices.

Figure 9 shows the dynamic consequences of well drilling on acreage and groundwater depth change.

Figure 9: Local projections of changes in crop acreage with a 1% increase in wells



Note: Each plot shows the dynamic effect of a 1% increase in wells in year t on either the depth to the groundwater table or the change in crop acreage, using local projections. The acreage plots are estimated with LP-IV. The error bars show 90 and 95% confidence bounds for Conley standard errors accounting for spatial correlation within 120 km and temporal correlation within 2 years (since it is a short panel).

The depth to the groundwater table increases continually after wells are drilled, at the rate of about half a foot a year for a one percent increase in wells. Total acreage stays the same, though it masks the trend of substitution across crop categories. Immediately, counties with new wells see more fruit trees and fewer low-water, low-valued field crops, and these trends increase over time. There is no change for high-valued annuals like vegetables. Overall, these trends suggest not only an increase in water useage in drought years, but also in an average year, as fruit trees can use several times as much water as low-water field crops like wheat.

5.5 Conclusion: wells change adaptation

In this section, I showed that wells

6 Private value of adaptation to surface water scarcity

6.1 Methods

I now connect the previous analysis of actions by estimating of the aggregated values of all adaptation actions. I closely follow the conceptual framework and Shrader (2023), by regressing the profit on components of surface water information. In conducting this analysis, we will learn about which period of adaptation most influences aggregate agricultural outcomes.

A limitation of studying the private value of adaptation is that the best profits data I have is at the county level, which is more aggregated than the surface water forecast information. Aggregating explanatory variables to their mean is the best way to handle this data structure, and the bias in the estimate can actually be low as the number of individuals in the group increases (Foster-Johnson and Kromrey, 2018).

$$Y_{ct} = \beta_1 s_{ct-1} + \beta_2 \varepsilon_{ct}^{\text{mid}} + \beta_3 \varepsilon_{ct}^{\text{late}} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{9}$$

I construct the ε_{ct} by determining which contracts exist within the county, and weighting the forecasts that correspond to those contracts by the proportion of water from each project in the county, approximated by the state's water model[15] (Department of Water Resources, 2022). In equation (9), the variation comes from the average surface water forecast experienced by districts throughout the state. The map in figure **??** shows that districts with similar forecasts are often clustered together, meaning that the composition of project contracts varies at the county level across the state.

Y_{ct} measures the crop-specific flow profit over all agricultural land in a county, not only districts with project contracts. I also look at total agricultural profits, which adds in livestock revenues and costs. For about 8.5% of county-years, the profit is negative, which I address in two ways. First, I transform Y_{ct} with the inverse hyperbolic sine function, which has approximately the same interpretation as a log transformation given the mean of my data (Bellemare and Wichman, 2020). Second, I use a tobit regression.

X_{ct} again controls for non-project water availability from streamflow, precipitation, and depth to the water table, as well as demand from temperature, sot that the βs can be interpreted as actually measuring the change in outcomes due to only changes in surface water forecasts. Other omitted variables include crop storage and government payments, which are correlated with revenues and surface water availability (Fisher et al., 2012); I control for these using crop inventory changes and aggregate government payouts from the BEA data.

By separating the equation (9) into components of information, it is easier to interpret where the variation is coming from, though I no longer directly condition on the final realization of the surface water shortfall s. To get the benefit of adaptation estimated in Shrader (2023) I transform the estimated coefficients so that the benefit of early adaptation (the profit effect of $\hat{s}$ conditional on s) is $\beta_2 - \beta_1$, and the benefit of mid-season adaptation (the profit effect of $\hat{s} + \varepsilon^{\text{mid}}$ conditional on s) is $\beta_3 - \beta_2$, and the direct effect of surface water scarcity is β_3.

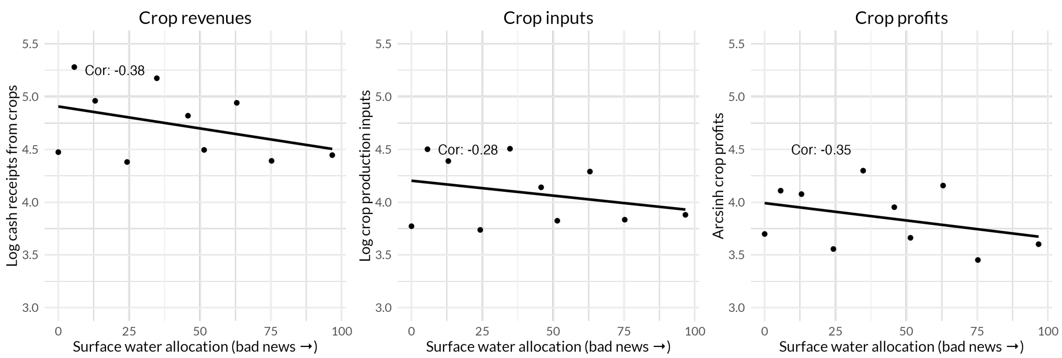
Finally, the framework provided by Shrader (2023) captures the benefit of adaptation given that forecasts exist, but says nothing about outcomes in the counterfactual case of not having the forecast at all. Without being provided surface water allocation forecasts, farmers would still adapt, but they would use other, perhaps lower quality information, to prepare for the surface water allocation. Learning about this counterfactual is useful for knowing the value of providing the forecast, which might allow for clearer policy recommendations. In my context, unlike for most weather forecasts, there is only one forecast clearly most relevant to the surface water allocation: the official forecast published by the entities that deliver the water. My context also features a three years where the US Bureau of Reclamation decided to wait longer than the preceding period to publish a forecast. In 1988, the USBR issued a vague initial surface water allocation forecast (no percentages announced) on February 15th, and announced percent allocations on February 23rd. Until that time, the first forecast had always been published by February 1st, and after 1988, it was published by February 1st again. In 2005, the US Bureau of Reclamation issued forecasts on February 23rd again, though this marked a permanent shift toward later forecasts. In 2016, the Bureau of Reclamation issued their first forecast on April 1st, deviating from their pattern of issuing a first forecast in the third week of April[16].

These temporary and permanent changes in forecasting policy result in natural experiment where the

[15]When a county has multiple contract types with the same project in one county, I take the average within the project

[16]In a conversation I had with the Farm Bureau, the director I spoke with called the delay in 2016 an "absolute disaster".

Figure 10: Binscatter of county-level crop revenues and inputs, on the surface water allocation, controlling for county and year fixed effects



Note: All variables are transformed before being binned, and in units of millions of dollars. For profits, I use the hyperbolic arcsin transform because 7% of observations are negative, which should be comparable to the others since the mean of profits is $318 > 10$ (Bellemare and Wichman, 2020). I measure crop revenues with cash receipts from crops, and crop inputs using the sum of all production expenses, excluding livestock purchased and feed purchased. For profits, I subtract the costs from the revenues.

forecast for a portion of surface water in some counties is delayed unexpectedly. I use a standard 2-period differences in differences design to study how profits for counties changed between the year before the forecasting time shock and after, based on a treatment level proportional to the quantity of a county's agricultural water coming from the Central Valley Project. Using three separate differences in differences is most straightforward here because each shock is preceded by a period of at least ten years with the same forecasting timing. Equation (10) formalizes my estimation strategy.

$$Y_{ct} = \alpha Q_c \times P_t + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{10}$$

Q_c is a continuous variable for the proportion of the quantity of agricultural water coming from the Central Valley Project on average, and P_t is an indicator for the year in which the Central Valley Project surface water allocation forecast was delayed. α_1 is the coefficient of interest, and it captures how much the profit Y_{ct} is affected by a marginal increase in the amount of the county's water subject to a delay. In the three differences in differences regressions, I use the years $t \in \{1985, 1986\}, t \in \{2004, 2005\}, t \in \{2015, 2016\}$.

6.2 Results

In figure 10 I show a binscatter of revenues, cost, and profits on the surface water allocation, all transformed with log or inverse hyperbolic sine to address the skew in the data. All three variables respond strongly and negatively to lower surface water allocations. Despite the lowering intensity of production, farmers experience lower profit in years where their county faces the lowest surface water allocations, meaning that surface water is important for farmers' outcomes.

Estimating the empirical specification from equation (9) will reveal how much of the decline in profits can be avoided from adaptation in different periods. The coefficient estimates from the regression for several specifications can be found in appendix **??**. Each component of information contributes negatively to profit, with the earliest information having the strongest effect. The results match the intuition from the raw data in figure 10, since bad surface water news lowers profit. However, as I explained in the previous methods section, if I difference the coefficients they can be interpreted as the private benefit of adaptation conditional on the actual surface water allocation. I plot this private benefit of adaptation in figure 11.

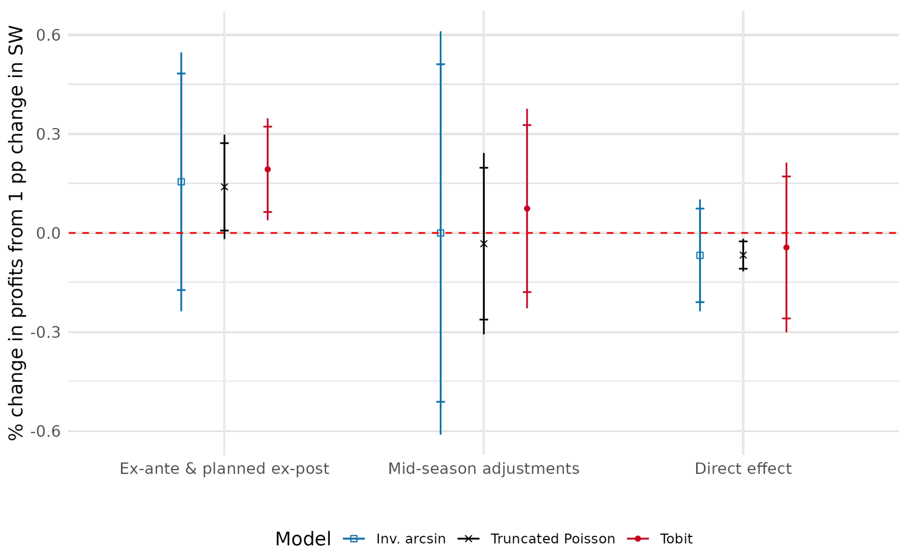
Figure 11 shows the private benefit of adaptation at two periods, when only the previous allocation is known (the left grouping of points), and after all districts get a surface water allocation (the middle grouping of points). As explained in the conceptual framework, the earliest adaptation in the year includes both ex-ante adaptation and expected ex-post adaptation. The news contained in the mid-season surface water allocation forecast allows farmers to adjust flexible adaptation strategies, and change plans for ex-post adaptation. The third group of coefficients shows the direct effect of a marginally higher surface water allocation shortfall on profits. I plot three specifications, and the coefficients in each specification can be approximately interpreted as the percent change in profits for a 1 percentage point change in the surface water allocation forecast or realization. With the different specifications, I seek to address the problems of having negative profits. The coefficients represented by the leftmost blue squares are estimated in a specification where I transform profits using the inverse hyperbolic sine function. I estimate the middle black x coefficients using PPML, where all negative values are truncated to zero. The rightmost red circles were estimated by logging profits, where I addressed truncation using tobit.

The coefficient estimates are fairly close across specifications, even though the statistical significance varies. Ex-ante and expected ex-post adaptation increases county crop profits by 0.16% for every one percentage-point drop in the surface water allocation forecast, relative to not being able to adapt, about $420,000 (2017 dollars) for the average county. Mid-season adjustments have no effect on profits. The direct effect of surface water allocation shortfall is negative, like expected, though may not be statistically significant. The magnitude of the direct effect of surface water allocation shortfall is about 1/3 as large as the adaptation effect. This means that net of adaptation, surface water allocation shortfalls have a small impact on farmers' outcomes. As shown with the non-transformed coefficients, the majority of farmers' profit outcomes are directly tied to adapting to lower amounts of water.

While figure 11 shows the benefit of adaptation, figure 12 gives suggestive evidence for the value of these surface water allocation forecasts for adaptation. I plot the main differences-in-differences effect, the α coefficient from equation (10), for each of three differences-in-differences regressions which cover a year when the US Bureau of Reclamation surprisingly delayed their first surface water allocation forecast. The coefficients show the percent change in profit if the county's agricultural water portfolio had one percentage point more water from the Central Valley Project on average. The average county gets 10% of its agricultural water from CVP on average, though some counties have 0% and some have up to 75%.

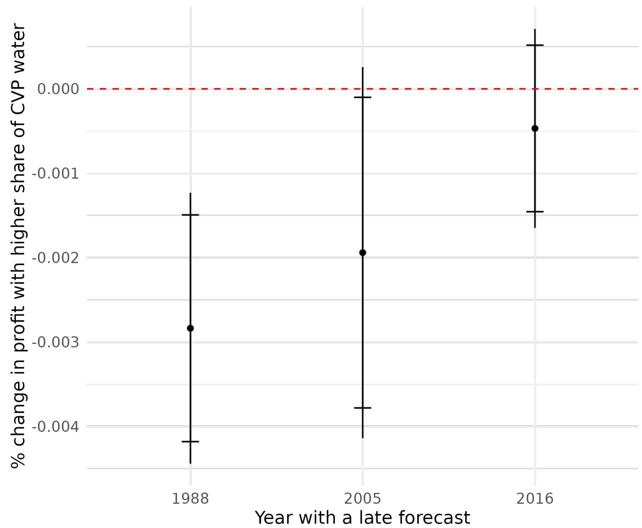
Overall, the delay of a Central Valley Project surface water allocation forecast decreased profit for counties with more CVP water in the year that the forecast was delayed. The coefficient estimate of the effect of the delay in forecast stayed negative for in all three years, but the magnitude declined and became less significant. The magnitudes also are small, overall. In 1988, for example, the delay cost the average county $70,000. The low magnitude is not surprising given that the private value of adaptation is much higher before the initial surface water allocation forecast in February, while the delays shift information within the less valuable adaptation period. Nevertheless, the estimates show that even though farmers have some information about surface water allocations, shifting the first official surface water allocation forward in time is privately costly for farmers. Therefore, in this study the surface water allocation forecasts not only

Figure 11: Private benefit of adaptation to surface water allocation shortfall



Note: These plots show the results of the estimations of equations (9), after transforming the coefficients so that I control for the effect of forecasts with the actual surface water allocation; specifically, the first group of coefficients show $\beta_2 - \beta_1$, and the second group shows $\beta_3 - \beta_2$, and the final group shows β_3. The 90 and 95 percent confidence intervals are transformed accordingly and plotted. The coefficients can be approximately interpreted as the percent change in profits for a 1 percentage point change in the surface water allocation forecast (first two groups) or realization (last group). The groups are arranged according to the timing of adaptation, with the earliest actions on the left; the x-axis explains how to interpret the actions that farmers take, according to the conceptual framework. Each group shows coefficients for three specifications which each address the problems of having negative profits in 8% of county-years. The coefficients represented by the leftmost blue squares are estimated in a specification where I transform profits using the inverse hyperbolic sine function. I estimate the middle black x coefficients using PPML, where all negative values are truncated to zero. The rightmost red circles were estimated by logging profits, where I addressed truncation using tobit.

Figure 12: How delays in surface water allocation forecasts affect profits



Note: These plots show the main differences-in-differences coefficient, α from equation (10), for each of three differences-in-differences regressions. Each regression covers a year when the US Bureau of Reclamation surprisingly delayed their first surface water allocation forecast. The coefficients show the percent change in profit if the county's agricultural water portfolio had one percentage point more water from the Central Valley Project on average. The average county gets 10% of its agricultural water from CVP on average, though some counties have 0% and some have up to 75%.

proxy for the quantity of surface water that farmers believe they will receive, but the forecasts deliver actual information that has value for farmers, and guides better private decisions. The diminishing in the value over time might show that farmers have developed ways to better predict the surface water allocations over time, or that they have insulated themselves from potential information delays.

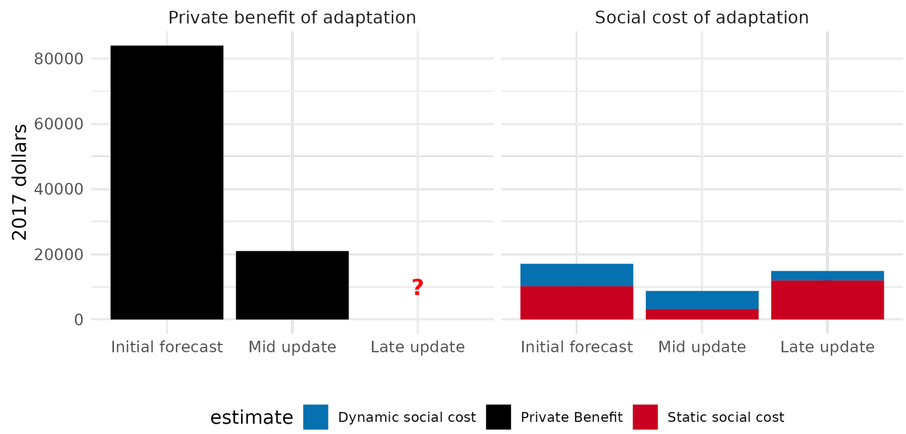
7 Aggregating the social cost estimates

I now take the previous estimates of changes in behavior to see how a one-unit change in the surface water allocation affects the dynamic path of groundwater use, both temporarily as well drilling catches back up to trend, and permanently, assuming that the persistent effect for the mid-year update in the local projections plot in figure 7 is truly above zero. I first estimate the increase in groundwater use from the change in the groundwater table, and then I compare these estimates with the implied change from crop choices.

First, there is an increase just from having access to new groundwater. A one percent increase in the surface water shortfall surface water allocation results in a 0.46% increase in wells, which remains excess for 1 year 78% of the time, two years 56% of the time, three years 34% of the time, and forever 28% of the time. A 1% change in wells results in a decline of the water table by about 0.16% a year, so the well change from a surface water allocation shock, multiplied by the average agricultural area in a district, and the average storage of the aquifer implies an average of 318 acre feet extracted over the time that the wells are excess after a shock from the initial surface water allocation, and 385 acre feet over the time the wells are temporarily excess from a mid-year surface water allocation update, and 18 acre feet per year forever.

Second, there is a groundwater increase from a change in crop planting patterns. The crop responses to

Figure 13: Marginal private value and social costs of agricultural adaptation for one district



new wells shows that districts plant more perennials, transitioning from both high water field crops (about 20% of the time) and low-water field crops (about 80% of the time). Even though some high-water field crops require the same amount of water as perennials, high-water field crops can be fallowed and so usually use less water overall, meaning that both of these transitions likely lead to water intensification. On average, about 27% of land is idled. Given the probability of idling, and the assumption that high-water annuals use the same amount of water as perennials, and low-water annuals use half, planting a perennial requires about 2.25 acre feet more water per year. Perennials are also a dynamic choice, so having a new well gives districts a head start in growing them and transitioning to the high water intensity crop. The average district has about 8500 acres in perennials, so that the new wells resulting from a marginal change in the surface water allocation would result in about 5 new perennial acres. Over the time that wells are excess, before well drilling catches up to trend, about 25 acre feet of groundwater is used in the district.

Figure 13 shows the summary of all of the findings in this paper. I combine the static social cost estimates from section 4, and the private benefits estimated in section 6 with the dynamic social costs from this final section. I assign a $40 per acre-foot value of groundwater used in California, which was the original (low) price mandated by the state of California to districts without an approved management plan under the Sustainable Groundwater Management Act (Vad, 2024).

Overall, the benefits of adaptation outweigh the social costs, though the social costs are not negligible. In the period of the initial surface water allocation information, the social costs make up about 1/4 of the private benefit of adaptation. In the middle of the planting season, the private benefit of adaptation falls much faster than the social cost. Although I cannot calculate the private benefit of ex-post adaptation at the end of the season, we might expect it to be a similar magnitude or lower than the mid-season update due to fewer adaptation options available.

8 Conclusion

In this paper, I find that farmers adapt to surface water scarcity using both water conserving and groundwater intensifying adaptation actions. Overall, farmers increase their groundwater extracted many times more than they decrease surface water use. Further, through well drilling, the increase in groundwater extraction is long-lasting. Although the private benefit of adaptation outweighs the social costs, the social costs are large in magnitude. This suggests that the overall benefits of adaptation in agriculture may be lower than initially thought, and that we might need to think carefully about how to incentivize socially beneficial private adaptation.

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Figure A.1: Four examples of how a farmer would encounter a surface water allocation forecast

Advance-Register

110th year, Number 321 — Tuesday, December 1, 1992 — Tulare, CA — 35 cents, tax included

City eyes new police station

Army paid $124 for 9-inch piece of string

TIP chief may work part time

Season chore

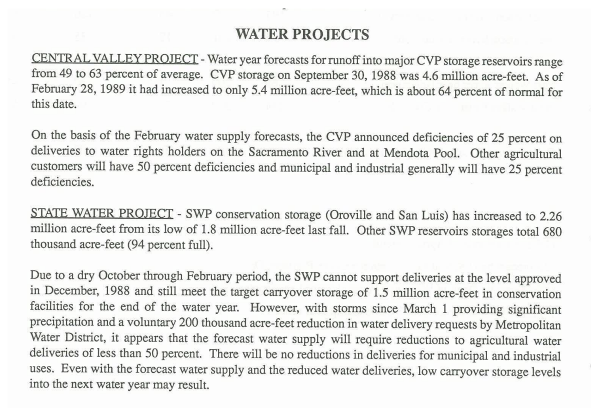
County reps discuss their fiscal plight

Snack tax ends, welfare cuts start

State Water Project delivery projected at only 10 percent

Excessive force case against police officers goes to trial

(a) Front page of December 1, 1992 Tulare Advance Register, with the State Water Project initial allocation making the bottom of the page



WATER PROJECTS

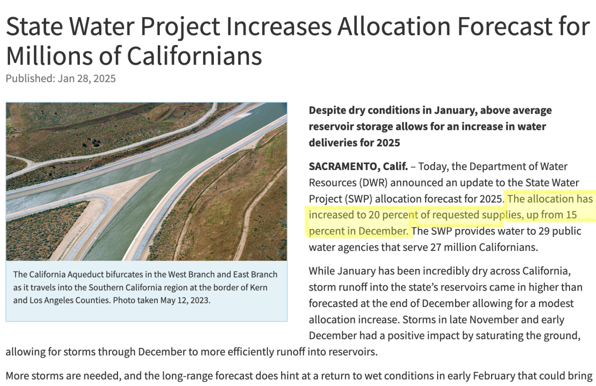
CENTRAL VALLEY PROJECT - Water year forecasts for runoff into major CVP storage reservoirs range from 49 to 63 percent of average. CVP storage on September 30, 1988 was 4.6 million acre-feet. As of February 28, 1989 it had increased to only 5.4 million acre-feet, which is about 64 percent of normal for this date.

On the basis of the February water supply forecasts, the CVP announced deficiencies of 25 percent on deliveries to water rights holders on the Sacramento River and at Mendota Pool. Other agricultural customers will have 50 percent deficiencies and municipal and industrial generally will have 25 percent deficiencies.

STATE WATER PROJECT - SWP conservation storage (Oroville and San Luis) has increased to 2.26 million acre-feet from its low of 1.8 million acre-feet last fall. Other SWP reservoirs storages total 680 thousand acre-feet (94 percent full).

Due to a dry October through February period, the SWP cannot support deliveries at the level approved in December, 1988 and still meet the target carryover storage of 1.5 million acre-feet in conservation facilities for the end of the water year. However, with storms since March 1 providing significant precipitation and a voluntary 200 thousand acre-feet reduction in water delivery requests by Metropolitan Water District, it appears that the forecast water supply will require reductions to agricultural water deliveries of less than 50 percent. There will be no reductions in deliveries for municipal and industrial uses. Even with the forecast water supply and the reduced water deliveries, low carryover storage levels into the next water year may result.

(b) A screenshot from the Department of Water Resources' snow survey published in March 1989 (these are published, February, March, April, May and October), and each of the early-year snow surveys include information like this, highlighting allocation decisions made by both projects



State Water Project Increases Allocation Forecast for Millions of Californians

Published: Jan 28, 2025

The California Aqueduct bifurcates in the West Branch and East Branch as it travels into the Southern California region at the border of Kern and Los Angeles Counties. Photo taken May 12, 2023.

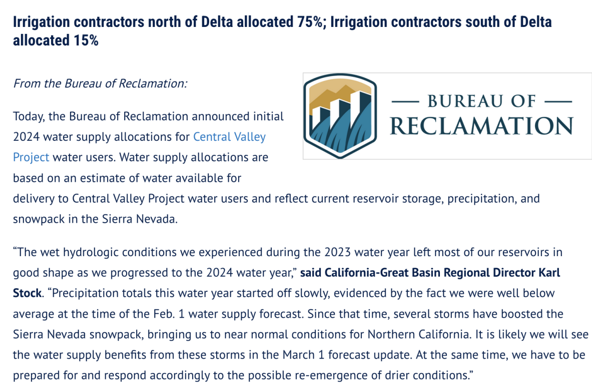
Despite dry conditions in January, above average reservoir storage allows for an increase in water deliveries for 2025

SACRAMENTO, Calif. – Today, the Department of Water Resources (DWR) announced an update to the State Water Project (SWP) allocation forecast for 2025. The allocation has increased to 20 percent of requested supplies, up from 15 percent in December. The SWP provides water to 29 public water agencies that serve 27 million Californians.

While January has been incredibly dry across California, storm runoff into the state's reservoirs came in higher than forecasted at the end of December allowing for a modest allocation increase. Storms in late November and early December had a positive impact by saturating the ground, allowing for storms through December to more efficiently runoff into reservoirs.

More storms are needed, and the long-range forecast does hint at a return to wet conditions in early February that could bring much-needed rain and snow.

(c) The State Water Project and Central Valley Project usually publish articles about their initial allocations and amendments on their websites



Irrigation contractors north of Delta allocated 75%; Irrigation contractors south of Delta allocated 15%

From the Bureau of Reclamation:

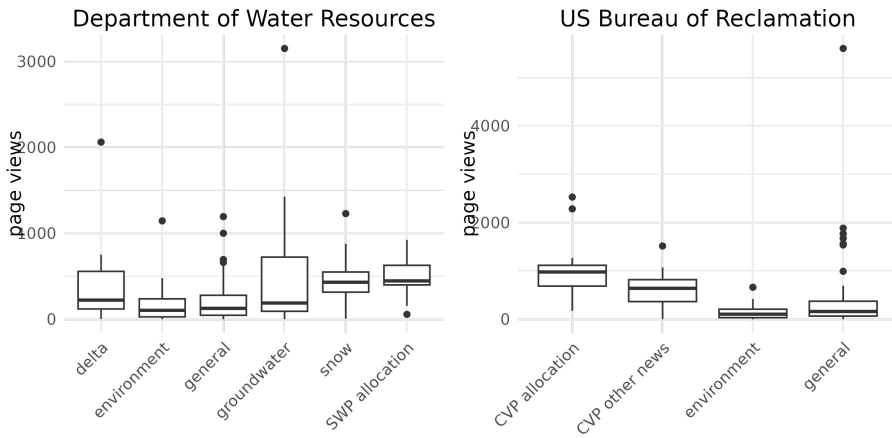
BUREAU OF RECLAMATION

Today, the Bureau of Reclamation announced initial 2024 water supply allocations for Central Valley Project water users. Water supply allocations are based on an estimate of water available for delivery to Central Valley Project water users and reflect current reservoir storage, precipitation, and snowpack in the Sierra Nevada.

"The wet hydrologic conditions we experienced during the 2023 water year left most of our reservoirs in good shape as we progressed to the 2024 water year," **said California-Great Basin Regional Director Karl Stock**. "Precipitation totals this water year started off slowly, evidenced by the fact we were well below average at the time of the Feb. 1 water supply forecast. Since that time, several storms have boosted the Sierra Nevada snowpack, bringing us to near normal conditions for Northern California. It is likely we will see the water supply benefits from these storms in the March 1 forecast update. At the same time, we have to be prepared for and respond accordingly to the possible re-emergence of drier conditions."

(d) Maven's Notebook calls itself 'California's Water News Central' and has aggregated USBR and DWR water allocation announcements since its inception in 2013.

Figure A.2: Page views by subject on California water news aggregator



Note: Distribution of page views by topic on Maven's Notebook, a California water news aggregator. News collected on May 1, 2025, spanning 5 years.

Table A.2: Surface Water Allocation Forecast Timing Summary Statistics

	SWP		CVP (south)	
Time Period	% with updates	Mean allocation %	% with updates	Mean allocation %
Near Feb 1 (Forecast)	97.96	38.39	53.06	40.50
Near Apr 1 (Forecast)	73.47	54.10	89.80	45.36
Near June 1 (Final)	46.94	60.00	63.27	60.77

Note: This is a summary of the surface water allocation forecasts that I observe, for the State Water Project and the southern portion of the Central Valley Project (which is representative of the timing of the other CVP regions).

A Data and Context

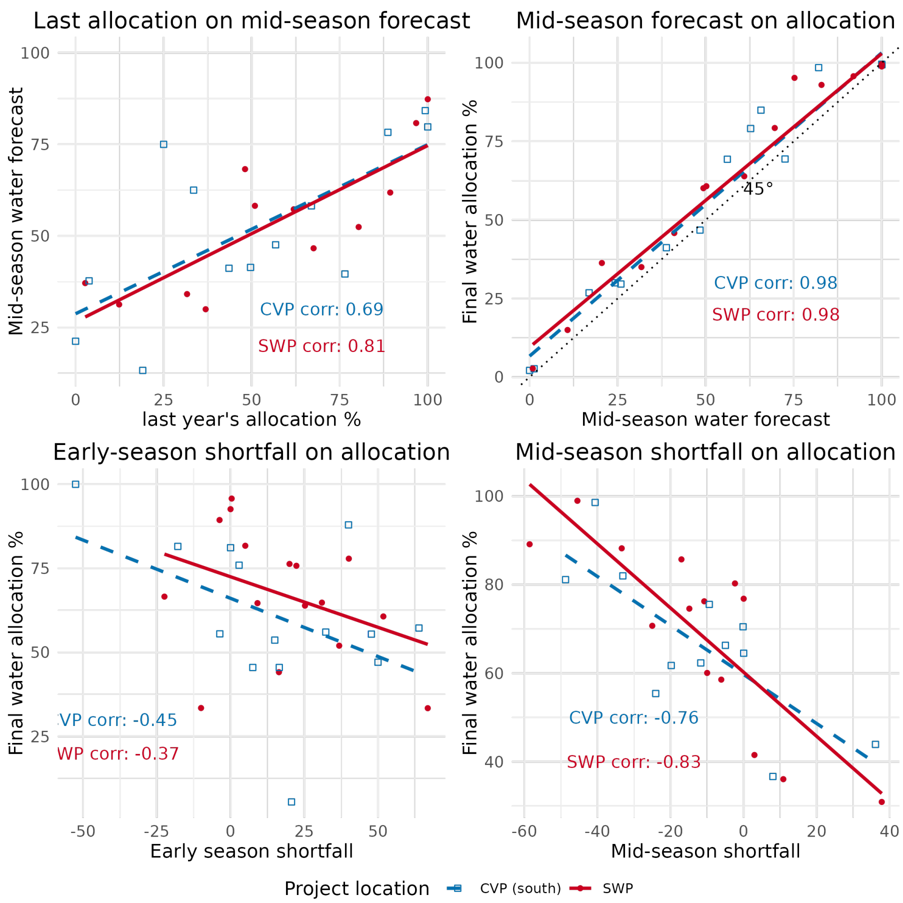
Over time, project allocations and announcements have changed in two major ways. The first is that allocations have generally decreased, in part because of drought, and in part because of environmental flows required under the Endangered Species Act[17]. Second, the 1993 Biological Opinion related to California's endangered fish recommended that the projects issue conservative water allocation forecasts (State Water Resources Control Board, 1995). Therefore, since 1995 the State Water Resources Control Board has asked the projects report the tenth-percentile statistic for the February allocation forecast. I show in the results section of the paper that the projects change in the

B Supplementary Results

B.1 LASSO results

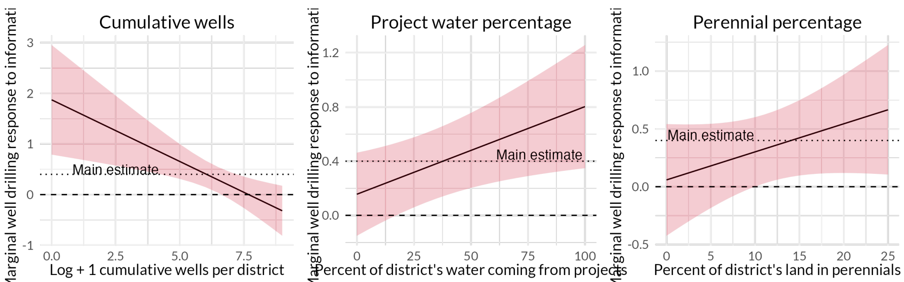
[17]Some species that have been protected include the Chinook salmon, delta smelt and steelhead trout (ICF, 2024)

Figure A.3: Relation of project forecasts to each other: across districts and across months in a year



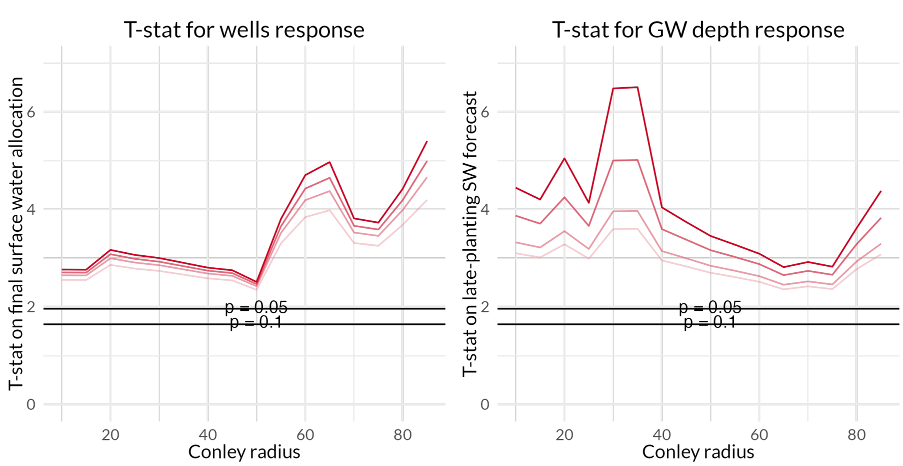
Note: The top left panel shows how the binned average of last year's surface water allocation percent corresponds to the average late-planting season surface water forecast (before April 1st) for the State Water Project (in red dots and solid line) and the Central Valley Project's southern districts, (blue squares and dashed line). I use the late planting season forecast because there is actual rather than imputed data in all years. There is a positive association between these data, showing that there is autocorrelation in forecasts over time. The lines also virtually overlap, showing that the autocorrelation of forecasts across projects is the same in expectation. The plot to the right shows an analagous pattern, exploring the relation between one year's late planting season surface water forecast and the same year's final surface water allocation. The points are highly correlated, showing that the delivery percent is predictable by mid-season. I also plot a dotted 45 degree line illustrating that forecasts are revised upward, although in the same pattern across projects.

Figure B.4: Heterogeneity of well drilling responses to information based on district characteristics



Note: To generate these plots, I run the main specification for the well drilling response regression, interacting each of the surface water forecast variables by the heterogeneity variables displayed in these tables, first the lagged log of the cumulative number of wells drilled in the district, second, the percent of district surface water from project sources, and third, the percent of district land planted in perennials on average. I show the estimated heterogeneous effect along with its 95% confidence interval. I display the main estimated coefficient without these interactions as the dotted line at y = 0.4. Overall, the response of well drilling is stronger when districts have fewer wells, depend more on project water, and have more perennials.

Figure B.5: T-statistic of main coefficient using spatial and autocorrelation robust standard errors



Note: These plots show the T-statistic of the main significant coefficients for the well drilling response regression and groundwater depth regression displayed in table B.3, which are on the final surface water allocation and late-planting season surface water forecast respectively. The x-axis shows a variety of Conely radii, and the darker lines represent the T-static for higher time lags, using 1, 5, 10, and 20. Overall, the main coefficients remain significant for any spatial radius and time lag displayed.

Table A.2: Typical crops at each planting time by region, and watering requirement

Region		**Early planting**	**Late planting**
Central Valley	Low Water	Wheat (170mm)	Corn (700mm)
		Carrots (150mm)	Tomatoes (650mm)
	High Water	Sugarbeets (220mm)	Rice (1100mm)
		Onions (500mm)	Cotton (1000mm)
Inland Desert	Low Water	Broccoli (140mm)	Corn (780mm)
		Wheat (270mm)	Squash (470mm)
	High Water	Watermelons (470mm)	Cotton (1200mm)
		Tomatoes (900mm)	Tomatoes (930mm)
South Coast	Low Water	Wheat (240mm)	Dry beans (370mm)
		Carrots (275mm)	Peas (150mm)
	High Water	Strawberries (800 mm)	Tomatoes (600mm)
		Garlic (475mm)	Corn (600mm)

	Revenues	Costs
Initial SW forecast shortfall	-0.04	-0.03
	(0.17)	(0.15)
Mid-planting SW update	-0.08	-0.01
	(0.10)	(0.08)
Late-planting SW update	-0.09^{**}	-0.07^{**}
	(0.04)	(0.03)
Omitted vars. controls	yes	yes
County FEs	yes	yes
Year FEs	yes	yes
SE cluster	Conley-Spatial	Conley-Spatial
Num. obs.	2208	2208
Pseudo R^2	0.97	0.96

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.3: Districts' adaptation responses to surface water allocation forecasts

1. Crop choice	Idle	Double	Early-low	Early-high	Late-low	Late-high
100% - last year's SW allocation	−0.07	0.00	0.24***	0.25	0.23***	−0.11
	(0.07)	(0.05)	(0.08)	(0.18)	(0.09)	(0.15)
100% - mid-planting SW forecast	0.48***	−0.08	0.07	0.06	−0.44*	−0.47***
	(0.10)	(0.06)	(0.12)	(0.25)	(0.25)	(0.11)
100% - late-planting SW forecast	0.23*	0.07	−0.20	−0.34	−0.26	−0.01
	(0.12)	(0.08)	(0.18)	(0.22)	(0.23)	(0.22)
100% - final SW allocation	0.10	−0.00	0.23	0.04	0.01	−0.12
	(0.15)	(0.10)	(0.15)	(0.14)	(0.29)	(0.28)
Omitted vars. controls	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Region-year FEs	yes	yes	yes	yes	yes	yes
SE cluster	district	district	district	district	district	district
Num. obs.	1614	1598	1614	1548	1539	1493
Pseudo R^2	0.96	0.94	0.93	0.86	0.94	0.96

2. Groundwater depth change	(1)	(2)	(3)	main	(5)	w/senior
100% - last year's SW allocation	−0.01	0.06	−0.02	0.06	0.06	0.15**
	(0.07)	(0.07)	(0.06)	(0.07)	(0.12)	(0.08)
100% - mid-planting SW forecast	−0.04	−0.04	0.06	−0.00	−0.00	0.15
	(0.11)	(0.11)	(0.10)	(0.11)	(0.18)	(0.11)
100% - late-planting SW forecast	0.19**	0.14*	0.21***	0.15**	0.15***	0.24***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)	(0.07)
100% - final SW allocation	−0.01	0.11	−0.03	0.10	0.10	0.07
	(0.09)	(0.09)	(0.08)	(0.09)	(0.11)	(0.08)
Specs. same as well choice						
Num. obs.	4899	4899	4893	4893	4893	9855
Pseudo R^2	0.78	0.80	0.78	0.80	0.80	0.80

3. Well drilling choice	(1)	(2)	(3)	main	(5)	w/senior
100% - last year's SW allocation	0.07	0.09	0.10	0.08	0.08	0.01
	(0.11)	(0.13)	(0.12)	(0.13)	(0.14)	(0.12)
100% - mid-planting SW forecast	0.01	0.02	0.01	0.01	0.01	0.07
	(0.13)	(0.16)	(0.12)	(0.16)	(0.20)	(0.15)
100% - late-planting SW forecast	−0.16	−0.10	−0.15	−0.13	−0.13	−0.07
	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.11)
100% - final SW allocation	0.27**	0.36**	0.30**	0.40***	0.40***	0.25*
	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)
Omitted vars. controls	no	no	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	no	yes	no	no	no
Region x year FEs	no	yes	no	yes	yes	yes
SE cluster	district	district	district	district	Spatial-HAC	district
Num. obs.	4459	4439	4453	4433	4433	8273
Pseudo R^2	0.58	0.59	0.59	0.60	0.60	0.66

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: This table shows PPML regressions of crop choice, groundwater depth and well drilling responses to surface water information learned during the planting season. The coefficients have been transformed to percent changes, and the standard errors are delta-method adjusted. The crop choice regressions vary only by dependent variable crop category, with observation counts differing as not all districts grow every crop type. Controls include alternate water sources (streamflow forecasts, precipitation, temperature, lagged groundwater depth and wells), and lagged perennial acreage to account for switching costs. Groundwater depth measures average annual depth to water table (feet), while well drilling counts total wells drilled February-August. Columns represent different specifications: (1) year and district fixed effects only, (2) district and year-by-climate-region fixed effects, (3) all controls (alternate water sources and neighbors' groundwater extraction and well drilling choices for the depth and well regressions respectively) with basic fixed effects, (4) all controls with strong fixed effects, (5) spatial/autocorrelation robust standard errors, and (6) includes senior project districts.

Table B.3: Multinomial logit: response of crop choice to forecast shortfall

	double	early	idle	late	non_ag
(Intercept)	21.066***	10.214***	9.343***	14.841***	6.009***
	(0.72)	(0.742)	(0.537)	(0.613)	(0.503)
100% - last year's SW allocation	1.224***	0.84***	0.446***	-0.008	0.035
	(0.071)	(0.076)	(0.055)	(0.056)	(0.047)
Mid-planting SW update	0.536***	0.294***	0.167***	0.008	0.064
	(0.071)	(0.077)	(0.057)	(0.056)	(0.048)
Late-planting SW update	0.612***	-0.089	-0.04	-0.292***	0.165***
	(0.081)	(0.086)	(0.064)	(0.063)	(0.059)
Log lag cumulative wells	-0.259***	-0.477***	-0.619***	-0.62***	-0.242***
	(0.017)	(0.018)	(0.014)	(0.014)	(0.013)
Rainfall	-0.001***	-0.002***	0	0	0.001***
	(0)	(0)	(0)	(0)	(0)
Temperature	-0.137***	-0.144***	0.067***	-0.126***	0.014
	(0.015)	(0.016)	(0.011)	(0.012)	(0.009)
Central Valley = 1	4.314***	3.175***	1.105***	5.056***	-2.537***
	(0.243)	(0.289)	(0.183)	(0.266)	(0.169)
Inland Desert = 1	4.57***	1.813***	4.207***	2.669***	1.694***
	(0.41)	(0.554)	(0.224)	(0.583)	(0.209)
Sierra Nevada = 1	8.742***	2.247***	3.014***	3.245***	7.044***
	(0.284)	(0.004)	(0.028)	(0.003)	(0.312)
South Coast = 1	3.44***	2.979***	1.016***	3.871***	-0.192
	(0.258)	(0.298)	(0.19)	(0.272)	(0.174)
GW depth in 2000	-0.533***	-0.446***	-0.479***	-0.513***	0.275***
	(0.02)	(0.021)	(0.016)	(0.016)	(0.019)
log(-1 * lag_depth)	0.087***	0.078***	0.183***	0.226***	-0.189***
	(0.024)	(0.026)	(0.02)	(0.02)	(0.022)
Log area (km^2)	0.166***	0.455***	0.507***	0.517***	0.462***
	(0.018)	(0.019)	(0.014)	(0.014)	(0.014)
Log groundwater use	-0.016***	-0.007	-0.022***	-0.005	-0.136***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
log(price_field)	-3.797***	-2.025***	-1.724***	-2.904***	-0.767***
	(0.15)	(0.157)	(0.115)	(0.128)	(0.103)
Log non-project ag water	0.006	0.024***	0.026***	0.026***	-0.058***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)

Note: This table shows a model of crop choice response to surface water allocation forecasts using multinomial logit. I include the same controls and surface water forecast variables, but since I omit fixed effects, all variables after temperature are to account for differences across districts and years.

Table B.3: Robustness checks: method of imputation

	Dep var = Wells drilled			Dep. var = GW depth		
	M.I.	Last year	No impute	M.I.	Last year	No impute
100% - last year's SW allocation	0.08	0.06	0.03	0.07^{*}	0.02	-0.01
	(0.10)	(0.12)	(0.15)	(0.04)	(0.04)	(0.05)
100% - mid-planting SW forecast	0.01	0.00	0.24	0.02	0.03	0.09
	(0.11)	(0.07)	(0.19)	(0.03)	(0.03)	(0.07)
100% - late-planting SW forecast	-0.10	-0.02	-0.21	0.10^{**}	0.10^{*}	0.04
	(0.14)	(0.11)	(0.27)	(0.05)	(0.06)	(0.11)
100% - final SW allocation	0.34^{**}	0.19	0.39	-0.02	-0.00	0.00
	(0.17)	(0.16)	(0.30)	(0.05)	(0.06)	(0.14)
Omitted vars. controls	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
Region x year FEs	yes	yes	yes	yes	yes	yes
SE cluster	district	district	district	district	district	district
Num. obs.	4567	4567	3178	4902	5031	3627
Pseudo R^2	0.60	0.60	0.63	0.80	0.80	0.81

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: This table shows the main regression specifications for wells drilled and groundwater depth as in table B.3, where I change the method of imputation for the mid-planting (February 1st) surface water allocation forecast. The first column for both dependent variables uses multiple imputation where imputations are grouped by contract type. The second column uses the previous year's final surface water allocation, deflated empirically to capture the bias in the early surface water allocation forecasts. The final column drops observations where there is no mid-planting surface water allocation forecast.

Table B.3: Robustness checks: dependent variable specification and fixed effects

	Dep var = Wells drilled						GW depth
	main	(2)	(3)	(4)	(5)	(6)	(7)
100% - last year's SW allocation	0.08	-0.12	0.06	0.12	0.05	0.12	0.02
	(0.13)	(0.19)	(0.11)	(0.13)	(0.11)	(0.15)	(0.04)
100% - mid-planting SW forecast	0.01	-0.10	0.05	0.01	0.02	-0.07	0.09
	(0.16)	(0.16)	(0.13)	(0.16)	(0.15)	(0.19)	(0.08)
100% - late-planting SW forecast	-0.13	-0.34^{**}	-0.02	-0.11	-0.10	-0.02	0.11^{**}
	(0.12)	(0.17)	(0.11)	(0.13)	(0.11)	(0.12)	(0.04)
100% - final SW allocation	0.40^{***}	0.47^{**}	0.31^{**}	0.37^{**}	0.28^{**}	0.36^{**}	-0.07
	(0.15)	(0.20)	(0.13)	(0.15)	(0.13)	(0.16)	(0.06)
Omitted vars. controls	yes	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes	yes
Region x year FEs	yes	yes	yes	yes	yes	no	no
Right type x year FEs	no	no	no	no	no	yes	yes
SE cluster	district	district	district	district	district	district	district
Winsorize level	99.5%	100%	99%	99.5%	99.5%	99.5%	N/A
Dep. var timeframe	Feb-Aug	Feb-Aug	Feb-Aug	Feb-June	Jan-Dec	Feb-Aug	N/A
Num. obs.	4433	4432	4432	4330	4443	8292	9855
Pseudo R^2	0.60	0.78	0.48	0.57	0.66	0.66	0.82

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: The first column shows the main well drilling specification shown in table B.3 for reference. The next four columns each change the well drilling variable. Column (2) shows the results without winsorization, and column (3) shows the results with stronger winsorization (99% instead of 99.5%). Column (4) decreases the time period of well completion I study to February-June, and column (5) expands it to the entire year. The final two columns use right-type by year fixed effects for the well drilling and groundwater depth regressions.