The benefits and costs of agricultural adaptation to surface water scarcity

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November 8, 2025

Abstract

I ask how farmers respond to surface water scarcity in California, a setting where they might adapt through socially costly actions like unregulated groundwater extraction, or water conserving actions like land fallowing. Using variation in region-specific sub-annual surface water forecasts, I empirically estimate that farmers increase groundwater use more than they conserve water, especially at the end of the planting season. Meanwhile, farmers make well investments at least partially in response to average declines in surface water availability, fundamentally changing their short-term adaptation choice set. After drilling, I find that farmers plant more water-intensive crops and conserve less water. My paper contributes one of the first studies of agricultural adaptation on a broad set of choices, revealing adaptation potential in drying agricultural regions globally. However, the social value of adaptation might be much lower than the literature, which ignores adaptation choices, suggests. By combining my estimates of actions with an extension of the methods to value adaptation, I estimate that a groundwater externality of $360 per acre-foot, roughly the market price of surface water, would fully offset the benefit of adaptation.

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Most major agricultural areas globally have experienced warming and drying on average over the last half-century (Lobell and Di Tommaso, 2025), as well as more frequent droughts (Hoover and Smith, 2025), meaning that short and long-term water stress will become pervasive in many regions. The future of global food production depends on how much farmers can adapt to these conditions. So far, the economics literature has found that adaptation recovers a moderate-at-best proportion of lost yields, estimated using methods that abstract away from adaptation actions[1]. Unless we know what actions farmers take to adapt to weather and climate shocks, we cannot make informed policy suggestions to improve on the dismal projections.

Further, the moderate yield recovery may actually overstate the true benefits of adaptation if farmers adapt primarily with unsustainable groundwater extraction. Groundwater is insufficiently managed globally, and extensively used in irrigation. Farmers apply groundwater on 38% of irrigated land (Nagaraj et al., 2021), and groundwater substantially declined in 36% of aquifers over the last 40 years[2] (Jasechko et al., 2024). If farmers adapt by applying groundwater unsustainably, their ability to adapt declines over time, resulting in diminished future adaptation benefits (Lemoine, 2018). Fishman (2018) and Hornbeck and

*Many thanks for the helpful comments from Serkan Aglasan, Eric Edwards, Todd Gerarden, Adrian Haws, Jeffrey Hadachek, Nick Hagerty, Michael Hanemann, PJ Hill, Katrina Jessoe, Dan Kaffine, Cathy Kling, Ashley Langer, Derek Lemoine, Matthew MacLachlan, Kyle Meng, Ben Norton, Ivan Rudik, Tiemen Woutersen, and Nicholas Vreugdenhil.

[1]Burke and Emerick (2016) find that long-run adaptation had no effect on yield losses from past climate change, while Hultgren et al. (2022) estimate that agricultural adaptation will reduce up to 30% of yield losses.

[2]Of course, this is only a proxy for a lack of management. It is theoretically possible for the optimal policy to be to deplete groundwater. However, there are no estimates for the actual percent of aquifers unmanaged globally. We do know that virtually no through 2022, virtually no transboundary basins, which cover multiple countries, were managed (Eckstein, 2021).

Keskin (2014) have documented how groundwater depletion leads to future drought sensitivity. Adapting through unregulated groundwater use also leads to common pool externalities and other physical externalities like saltwater intrusion (Goebel et al., 2019), arsenic leaching (Smith et al., 2018), infrastructure damage through subsidence (Borchers et al., 2014), declines in neighboring wells (Sears et al., 2017), and a permanent decrease in aquifer storage capacity (Smith and Majumdar, 2020). The externalities are costly and might severely diminish the social benefits of adaptation deriving from yield increases.

In this paper, I ask "how do farmers adapt to surface water scarcity?" The answer informs us not only about how adaptation occurs currently, but also whether current strategies are sustainable over time or socially costly. I study farmers in California, a context where farmers already face yearly surface water uncertainty, long-run declines in surface water availability, and a historically unmanaged aquifer, common ingredients in agriculture under climate change. These farmers might take two broad types of actions in response to expected and realized surface water scarcity. The first is water conservation, where farmers lower their total water use. Since I cannot observe water application directly, I study land fallowing and crop switching as conservation outcomes. The second type of action is groundwater intensification, where a farmer shifts her surface water use to a substitute water source. I study change in depth to the groundwater table as a proxy for extraction, and well drilling as groundwater intensifying outcomes.

I aim to measure how much farmers take each type of action in preparation for future surface water scarcity. I can estimate the adaptation response empirically because California has variation in forecasted surface water scarcity that differs over the state and across years. Over 200 water districts have contracts from the state or federal government for surface water deliveries in the dry summer growing season. Because of exogenous differences in snowpack which differentially fill reservoirs, water districts will receive different amounts of surface water. The government aids farmers' decision-making through providing surface water allocation forecasts. The first comes out in the early planting season, and then is updated in the mid and late planting season.

I construct one of the broadest datasets of adaptation choices yet compiled, including district-level crop choices, land fallowing choices, change in depth to the groundwater table, well drilling, and various proxies for water application, combined with surface water forecasts and updates spanning from 1967 until 2022. I regress the cumulative levels of adaptation actions for a water district between the beginning of the year and summer on the initial forecast and two surface water updates. The coefficient on each of the three components of surface water information identifies the amount of an adaptation action resulting from a marginal surface water allocation change announced in the early, mid and late planting season, which accounts for farmers' choice sets changing over the planting season.

I find that farmers adapt with both water conservation and groundwater intensification. Specifically, a 1 percentage-point decrease in the surface water forecast leads to a 0.25% decrease in high water acreage, a 0.2% increase in low-water acreage, a 0.26% increase in idled acreage, a 0.22% increase in well drilling and a 0.08% increase in the depth to the groundwater table on average. My estimating strategy also recovers trends in adaptation across a planting season. Both the crop idling and groundwater extraction responses are highest at the end of the planting season. Using evapotranspiration, a proxy for total water application, as a dependent variable, I can both support and explain my results: in the early and mid planting season, adaptation generally tends to lower total water use. Farmers switch crops and likely plan for lower water application. However, by the end of the season, news about higher water scarcity tends to increase water application in general, consistent with groundwater extraction being one of the most flexible adaptation options left. Therefore, with late-season surface water shocks, farmers not only replace the entirety of their surface water shortfall with groundwater, but even exceed it. Adaptation through groundwater use is pervasive in the setting.

My results also showed that farmers drilled wells in response to a surface water allocation shock, suggesting that the groundwater intensity of adaptation might even increase. In order to tie the wells drilled to adaptation, I need to identify when those wells would have been drilled absent the surface water shock, important for actually estimating social costs of adaptation. I use local projections (Jordà, 2005) to trace out the cumulative change in wells from a surface water allocation shock in a given year. I find that the farmers who drilled in response to a shock did so about three to five years earlier than they otherwise would have[3]. The shift forward in time represents a real social cost because having a well likely changes farmers' future water use choices. After drilling, farmers gain access to the choice to extract (more) groundwater, which permanently lowers the marginal cost of surface water during drought, and therefore the risk of high prices.

To be able to estimate the change in the groundwater intensity of adaptation following a well being drilled, I conduct two additional empirical analyses. The first captures how the sensitivity of the adaptation actions to surface water scarcity from the main specification changes as the district's well stock increases. I take the main estimating equation and interact the three periods of surface water information by the lag of the cumulative wells in a district. I find that water conserving actions decrease as the well stock increases. Further, farmers become much less sensitive to surface water information early in the planting season relative to later in the planting season, which can be explained by the value of preparation decreasing because wells offer certainty in groundwater availability.

Second, I study how new wells affect the types of acreage planted. If the stability in water prices induces farmers to plant more perennials, the value of adaptation through groundwater also increases through the higher opportunity cost of fallowing. The challenge of estimating new acreage caused by wells drilled is that both choices are made simultaneously, as the future expected value of perennials factors into the crop decision and well decision. Therefore, I use exogenous changes in well drilling costs as an instrument for new wells. My main instrument is the interaction of the lag of the number of well drilling contractors in a district (competition) and annual steel pipe prices (a necessary input). Even the first stage reveals important information for adaptation: I recover how aggregate well drilling responds to a change in well value, through the cost. Overall, I find that a 100% increase in the price of steel pipe, about a 5% increase in the total cost of a large well, results in about 0.65 fewer wells per district in an average year, nearly a 10% decline on average.

In the second stage I estimate the local average treatment effect for the subset of farmers with well values somewhat close to the threshold of drilling, in a year where surface water scarcity is not necessarily high. Since crop choice might change over a few years after a well is drilled, I use the exogenous new wells as a shock in a local projections framework (Jordà et al., 2015). After a 'surprising' new well is drilled in a county, I find that total acreage increases by 400 acres within 2 years. Overall, the new acreage comes from perennials, which actually increase by more than 450 acres. Vegetables, a high-value annual crop, declines after new wells are drilled. The shift suggests that the way that groundwater lowers downside risk is incredibly valuable to farmers. The results are in line with estimates in the appendix showing that farmers

[3]Although short run shocks do not result in permanent new wells, long-run surface water declines do. In an appendix analysis, I use show that an exogenous permanent decline in surface water deliveries permanently increases the well stock. My estimates imply that 8.5% of wells drilled annually are directly because of long-term scarcity.

extract about 1800 acre feet per year on the average new well, enough to irrigate 450 acres with about 3.5 feet of water per year, sufficient for many perennials. Overall, my results all point to farmers adapting primarily and increasingly through groundwater use.

What is the social consequence of farmers adapting extensively through groundwater extraction? It depends on the full external cost of groundwater use, and there are no estimates for this value. However, I can compare the private net benefit of adaptation with the changes in groundwater use to back out the size of the externality that would cancel out the social benefit of adaptation. I estimate the private net benefit of adaptation using the conceptual framework laid out in (Shrader, 2023). In the baseline framework, I would regress farm profits (available at the county level) on the surface water allocation forecast and realization, and the coefficient on the forecast would recover the value of adaptation. In my context, farmers make choices based on multiple forecasts across the planting season, so I update the framework for multiple decision periods. Also, since farmers tailor their adaptation investments specifically to the level of surface water expected, I modify the baseline framework so that the benefit of adaptation is measured by a forecast becoming marginally more accurate rather than by a forecast marginally increasing. In practice, I simply interact the forecast by an indicator for whether it over-estimated or under-estimated the final surface water allocation.

I find that a marginally more accurate surface water allocation forecast would improve county level income by about \$400,000 early in the planting season, and \$500,000 in the mid-planting season, though the difference between the estimates is not statistically significant, showing that adaptation remains similarly valuable throughout the planting season. Overall, my results show that farmers' private benefit of being able to adapt marginally better is about 0.2% of total county profits, which should be scaled given that allocation forecasts only affect 47% of cropland. Conditional on adaptation, realized surface water scarcity has no effect on profits, consistent with farms essentially choosing their profit given their knowledge of water conditions.

I next compare the private net benefits of adaptation with the increases in groundwater use estimated earlier. Unfortunately, the empirical framework cannot recover the private benefit in the period where groundwater extraction most increases due to surface water scarcity. However, I make the reasonable assumption that the net private benefit of adaptation is bounded above by the mid-planting season adaptation value, since the number of adaptation options steeply diminish after the mid-planting season, and since the direct effect of surface water scarcity is zero. Therefore, a $\sim 0.4\%$ increase in district-level profits from adaptation would come at the expense of ~ 250 acre feet of groundwater use. Weighting county agricultural profits by the size of water districts, I find that a \$360 dollar-per-acre-foot externality would fully cancel the net private benefit of adaptation. \$360 is less than the highest price that some Groundwater Sustainability Agencies began charging for groundwater use above sustainable yield under the Sustainable Groundwater Management Act since 2024, a proxy for the district's belief about the local external cost of groundwater.

Ultimately, I show that understanding the mechanisms of agricultural adaptation is key to correctly estimating adaptation's benefit in the presence of unregulated resources. Farmers in California will face a decreasing ability to adapt in the long run, at the same time that surface water quantities continue to decline and become more irregular. Further, as farmers are already facing consequences of climate change, they are pressured to adapt more than previously, exacerbating future declines in adaptation.

My paper contributes to the climate adaptation literature in three ways. Carleton et al. (2024) explains that the literature exists in two independent strands, the first describing mechanisms of adaptation and the second identifying the value of adaptation broadly in order to correctly estimate climate damages. I contribute to both strands and act as a rare bridge across the two, showing that the mechanisms fundamentally affect the value of adaptation.

First, I contribute to the literature on forecasts for ex-ante adaptation, which finds that anticipatory responses substantially reduce weather-related damages (Molina and Rudik (2022), Shrader et al. (2023), Downey et al. (2023), Shrader (2023)). My paper adds to the literature in three ways. I modify the baseline framework of Shrader (2023) by estimating the benefit of adaptation across multiple intra-annual periods, potentially useful in agricultural adaptation where actions vary across the year. Second, I join Anand (2023) in adding more evidence for the importance of lead times in forecasts in some contexts, challenging the theoretical model of Millner and Heyen (2021), which concludes that long-run predictability becomes irrelevant when people can continuously adjust their actions. Third, I am one of the few studies to examine the value of adaptation through forecasts in an agricultural setting, despite agriculture being the industry most affected by climate change. Burlig et al. (2024) also studies agriculture, but examines the value of the forecast itself, rather than using the forecast to identify the value of adaptation. Fourth, I study how long-run adaptation (well drilling) affects agents' responses to forecasts for the first time.

On the mechanisms side, I undertake the broadest study of farmers' adaptation actions, contributing to our knowledge of how farmers adapt. Other papers have estimated a few of the potential mechanisms, either showing what actions are effective for promoting climate resilience, or what farmers actually do in response to weather shocks. Michler et al. (2019) and Auffhammer and Carleton (2018) showed that conservation agriculture practices reduced farmers' sensitivity to climate shocks. Fishman (2018) and Hornbeck and Keskin (2014) showed that investment in wells and groundwater extraction led or will lead to more sensitivity to drought. Blakeslee et al. (2020) find little evidence of farmers adapting to long-run water scarcity within agriculture, instead shifting industries. Burlig et al. (2024) and Hagerty (2022) both examine multiple adaptation choices, though neither examines a socially costly adaptation directly. I have the only paper studying both conservation and groundwater intensification choices, and both long and short-run decisions, comparing the uptake, consequences and value of both.

Crucially, my paper shows how bridging the two literatures is key to understanding the value of adaptation. Deschenes (2022) is the only other paper I am aware of has studied both strands at the same time, showing that adaptation to increasing temperatures decreased mortality but increased electricity use and hence emissions. However, Deschenes (2022) neither directly measures uptake of the long-term adaptation strategy (air conditioner adoption) nor calculates the actual benefit of adaptation. Otherwise, the literature assumes that the value of adaptation comes from private actors optimizing over an abstract choice vector, using the envelope theorem to argue that adaptation choices do not affect first-order benefits (e.g. Carleton et al. (2022), Shrader (2023)). Papers valuing adaptation this way also typically use yield as a dependent variable, which is not directly tied to farmers' welfare (Schlenker and Roberts (2009), Burke and Emerick (2016), Hultgren et al. (2022)). My paper reveals the previous methods of estimating aggregate adaptation fail to capture the actual benefits. Farmers change their adaptation strategies across a season, reflecting changing private costs over time, and unregulated groundwater extraction has non-trivial external costs.

In addition to the climate adaptation literature, my paper contributes to the water economics literature. A growing area of the literature studies California's complex water institutions(Hagerty and Bruno (2024), Bruno et al. (2024), Bruno and Jessoe (2021), Ayres et al. (2021), Hagerty (2023), Regnacq et al. (2016)). I am one of the first papers to study the surface water allocation forecasts specifically, public information predicting public water availability, which concerns about 19% of annual agricultural water. I also add to the literature on the substitution between groundwater and surface water. These resources are close to perfect substitutes for inputs, but there is a wedge between the private and social value of these resources. Much of the empirical work in the area examines the hydrological connection between surface water and groundwater (Kuwayama and Brozović (2013), Wheeler et al. (2021)), but less is known about the elasticity of substitution between the resources. Ferguson (2024) estimates the elasticity of substitution in California using the state's estimates of water use, while I study substitution over time through local well investment choices.

The paper proceeds as follows. Section 1 covers the essential background, while section 2 covers the data. Section 3 estimates the how farmers adapt in the short-run, and section 4 explores the consequences of well drilling. Section 5 describes the conceptual model behind estimating the net private benefit, and applies the conceptual model to empirics. Section 6 ties together the results in a discussion of the net private benefits and external costs of adaptation, and section 7 concludes.

1 Background

1.1 California's agriculture and climate

Ample sunlight, mild winters and fertile soil has made 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 (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).

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

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)).

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). The forecasts have been disseminated through newspapers, bulletins, and websites. Appendix figure A.2 shows examples of what the surface water allocation forecasts have looked like through time. Low surface water allocation forecasts are especially salient, making front page news in many agricultural communities. Figure A.3 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.

In addition to yearly surface water uncertainty, long-term surface water availability has decreased over time, and will continue to decrease. Between 2000 and 2020, the April 1st Sierra snowpack was only 80% of the 1950-1980 average, and snowpack is expected to decrease by 48-65% of the historical April 1st average by 2100 (California Department of Water Resources (2025a), California Office of Environmental Health Hazard Assessment (OEHHA) (2024)). Project water allocations have also been declining about one point per year since 1975 to reflect the reality of lower surface water availability. One surprising, and permanent surface water shock occurred during my study period, allowing a rare way to identify adaptation to long-run changes in surface water availability. In 1992, the Central Valley Project Improvement Act redistributed 14% of CVP

[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 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)

water from contractors to environmental uses in order to comply with the Endangered Species Act (Water Education Foundation, 2025). The State Water Project was also affected due to the coordinated operations of the projects (McClurg and Sudman, 2000). I plot a summary of the variation of surface water allocations within years and across years in appendix figure A.1.

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. 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. However, 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 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: adaptation in a year and over time

Now, I combine the pieces of the context to motivate how to study how farmers adapt to surface water scarcity. I previously showed that surface water scarcity occurs both in the short-run, through uncertain yearly surface water availability, and in the long-run, through persistent declines in surface water availability. Thus, profit-maximizing farmers would respond though annual and long-run adjustments. I first characterize the profit-maximizing problem in words to show how to conduct the empirical analysis of both timeframes of adaptation.

[7] Individuals hold less than 1% of water.
[8] Permits are virtually always granted.
[9] From the testimonies of two well drilling contractors.

A farmer aims to maximize her lifetime profits from crop production given exogenous, uncertain yearly surface water which also has a long-run shift in availability. The farmer's choices of short and long-run inputs respond to the changes in surface water. In a simple dynamic optimization setting where short and long-run adaptation options are separate inputs into a production function, we can separate the short-run adaptation problem from the long-run one. Even while dynamically optimizing, a farmer still sets the marginal benefit of short-run adaptation to the marginal cost of short-run adaptation. Therefore, I study the short-run adaptation problem separately from the long-run adaptation problem.

By exploring a farmer's short-run adaptation to surface water scarcity, I learn about how farmers adjust when exposed to surface water shocks, something that is currently unknown in the literature. Intuitively, how a farmer can adjust depends on when in the planting season she learns information. At different times within a year, the choice set changes due to timing constraints and previously fixed decisions. 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. Thus, even a farmer's yearly adaptation is a decision problem with several periods.

Grounding this in reality, there is an early planting season, spanning from October to December, a mid planting season, spanning from January to March, and a late planting season, running from April until the start of the dry season in June. Then, the dry season / harvest season continues until September. In each of the three periods before the dry season, farmers receive new information about surface water available to them in the dry season, which becomes more accurate as the dry season approaches. In each planting period, farmers can make a variety of short-run decisions. 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 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 period, regardless of past decisions, farmers can choose to abandon crops by ceasing to water what was already planted. By the time the dry season arrives, the only options left for adjusting to surface water supply shocks are crop abandonment and groundwater extraction. Through my empirical analysis, I will learn whether farmers actually use these different options, and to what degree.

In figure 1, I summarize the farmer's short run problem in a timeline, which illustrates how the timing of precipitation and information aligns with the decisions available to the farmer, highlighting why the private value of different adaptation decisions change over a year.

Then, there is long-run adaptation through well drilling. The benefit of a well is the sum of discounted additional profits from having access to groundwater forever, which is partly determined by the long-run expectations of dry-season surface water. In general, surface water availability has been declining, though it is not straightforward to find variation in long-run beliefs about surface water availability to measure how surface water availability affects wells. A large portion of the value of wells also comes from the price of crops. Since high-water intensity perennial crops increased greatly in value over time, the overall value of wells has also exogenously increased. 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 irreversibility of the fixed costs of investment, plus the uncertainty of future surface water availability means there is an option value of drilling.

Although well drilling is a long-run decision, a well is drilled within a particular year. Short-run surface water information can have an effect on well drilling by changing the current year's payoffs from a well, which matters if well value is increasing across farmers generally. 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. 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. Wells also affect short-run adaptation by giving farmers the choice to substitute with more groundwater, rather than conserve surface water.

Empirically, we do not know how much farmers respond to long-run water scarcity by drilling wells. Farmers without wells have a lower well value than farmers who do have wells. If the marginal product of water is low enough for farmers without wells, we will see them exit farming rather than drilling. Otherwise, declines in surface water availability should lead to drilling.

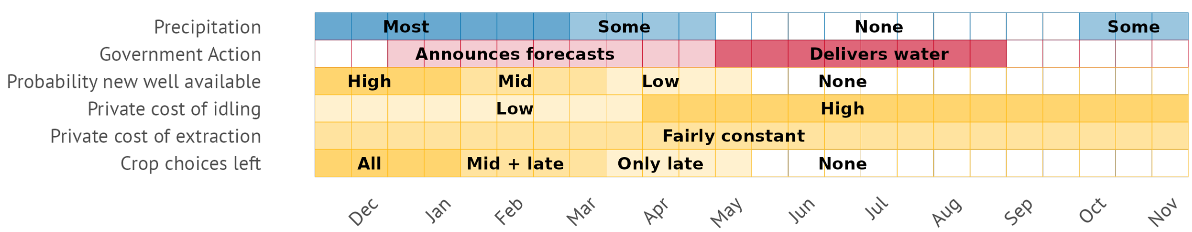
Understanding adaptation choices is important for informing policy and for exploring the viability of agriculture under higher surface water scarcity. However, knowing farmers' choices is also important for estimating the social costs of adaptation. Well drilling and groundwater extraction result in large unpriced externalities. New wells are particularly socially costly because having a well decreases the marginal cost of water in dry years and decreases the risk of high surface water prices (if farmers purchase surface water from the market), which might result in a more water intensive crop mix and thus more water use every year, and fewer water conserving choices made in dry years. 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 surface water. To understand the full picture of adaptation and its external costs, I explore the consequences of well drilling, the timing of drilling decisions, and the relative level of water conserving and groundwater intensifying actions.

2 Data

2.1 Unit of observation: 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 (2025b), Department of Water Resources (2025a)). 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 2 shows the geographical distribution of districts,

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



Note: The figure summarizes the background, and illustrates the different timing of information and environmental conditions that contributes to the complications in the farmer's annual adaptation problem. The top line shows the timing of precipitation in the year, showing no precipitation in the dry season. The second line shows the government's main interventions. They announce forecasts for surface water allocations prior to the dry season, and then deliver water during the dry season. The next four rows show facts about the four adaptation actions. The first is the probability that a well drilling decision will result in a new well usable during the current year's dry season. The probability decreases as the dry season approaches because of demand queues and permitting. The next adaptation is idling. Early idling decisions are privately cheaper because the farmer never planted any crops. Late idling decisions are expensive because they are equivalent to crop abandonment, meaning the farmer lost her investment. The private cost of extraction stays fairly constant throughout the season. The bottom row is annual crop choices. Early in the planting season, the farmer can still choose whether to plant in early, mid, or late-season crops. As time continues, the choices diminish.

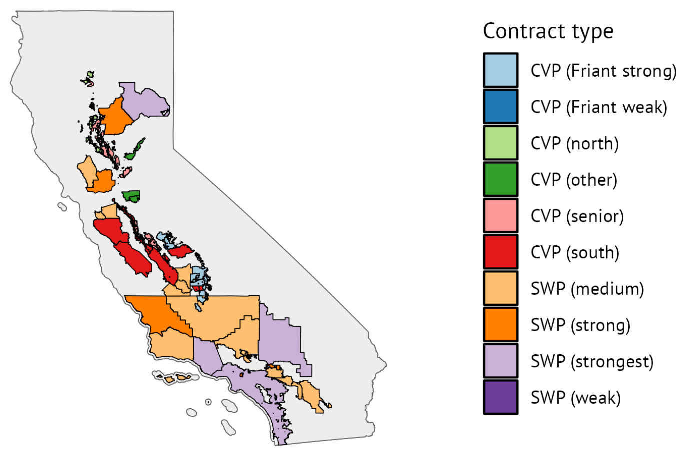
where the colors differentiate the project contracts that each district has, and therefore the surface water forecast they receive. There is slightly more variation in the data than is present on the map because the CVP Friant, SWP alternate, CVP senior, and CVP other categories each have multiple types 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).

2.2 Treatment variable: 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

Figure 2: Districts with surface water project contracts



Note: The map shows the project districts in the sample, colored by the broad contract types which govern their allocation forecast. The contract type explains whether the district gets Central Valley Project (CVP) water or State Water Project (SWP) water, along with the canal or seniority associated with each contract. There is more variation than what is present on the map. CVP (other) makes up 3 types of contracts, and each SWP district can technically have its own forecasting seniority.

beyond, February 1st, April 1st and June 1st. Table A.1 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.5, 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% 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].

[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.

[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/`

2.3 Water conservation choices: crop choice and land fallowing

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 times for vegetables across the four climate regions in the right panel of figure 2 (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%).

2.4 Groundwater intensification choices: well drilling, groundwater extraction and total water application

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.

I proxy for groundwater extraction using changes in depth to the groundwater table, data that has been collected for decades. 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

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

[13] 82% of wells include a purpose.

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, 2025b). 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.

I also collect a variable for total water application to compare overall conservation and groundwater intensification. A major way farmers adjust water is through the amount of application on their fields (Burlig et al., 2020). Like most regions, California has no data for actual water application. The best proxy for water application across my entire period comes from an 800-meter grid of evapotranspiration from Reitz et al. (2023). Evapotranspiration measures plant transpiration and the evaporation of water from all surfaces measured in meters per year, proxying for applied water in dry locations. The authors use machine learning to train a model of evapotranspiration including remotely sensed evapotranspiration data beginning in the 2010s, ground-level observational data beginning in the 1990s, and regional water balances through the 1880s. The output is the best existing estimates of water application over time.

2.5 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).

3 How do farmers adapt to short-term surface water scarcity?

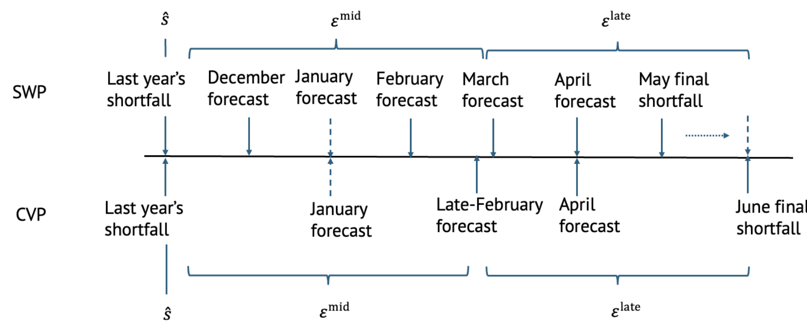
3.1 Methods: an empirical model of sequential adaptation

The goal for the main analysis in my paper is to estimate the portion of a district's (summer) dry-season adaptation level deriving from a surface water supply shock occurring at a specific time in the (spring) planting season. During the dry season, the only surface water available is an uncertain quantity delivered by the state or federal government through canals, and natural streamflow. Farmers can prepare for annual surface water scarcity because they receive forecasts about water deliveries.

For the remainder of the paper, instead of surface water allocations I will use 'shortfalls' as a more intuitive measure of scarcity. A shortfall is defined as 100% - the surface water allocation forecast percentage.

I can identify actions taken due to surface water shortfall forecasts from a particular time in the growing season because the government announces different shortfall forecasts to different districts at several points in the planting season. However, since some districts have contracts with the federal government, and some have contracts with the state government, the forecast announcement times are not consistent for all

Figure 3: Timing of forecasts from different projects



Note: This figure shows when each project tends to announce its forecast information. The arrows in the figure show when each agency announces a forecast. The forecasts on the top of the timeline are announced by the SWP, and the bottom ones are announced by the CVP. Dotted lines reflect times when forecasts are only sometimes announced.

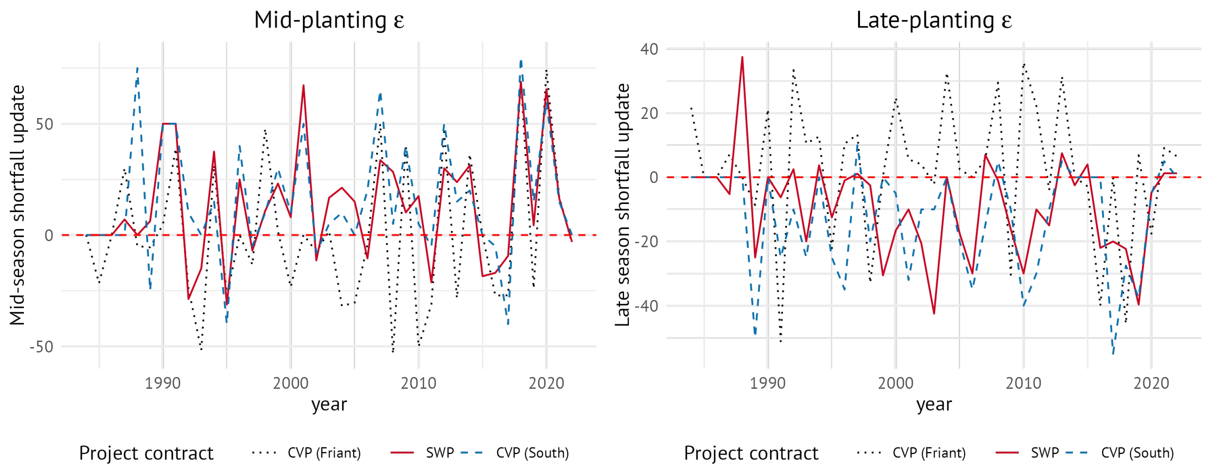
districts. I summarize the average forecasting behavior of each government and the choices that I make when constructing shortfall variables in figure 3.

The arrows in the figure show when each government agency announces a forecast. The forecasts on the top of the timeline are announced by the SWP, and the bottom ones are announced by the CVP. Dotted lines reflect times when forecasts are only sometimes announced. I choose my surface water shortfall variables according to two criteria. First, baseline information should be available to all districts when they start making planting decisions. Noticeably, the first forecasts for the CVP occur relatively late in the planting season. I choose the previous year's shortfall as the baseline information $\hat{s}$ in the main specification since it is the most comparable early information relevant to both types of contracts[14]. Second, information should be consistently announced to all districts, and far enough apart to retain sufficient variation. Therefore, I use the forecasts announced around late-February or the beginning of March, and also immediately prior to the dry season around May and June. I define shortfall 'updates' as the differences between the newest and previous forecast. The mid-planting-season update is given by ε^{mid}, which is the difference between the March shortfall forecast and the baseline shortfall forecast, and the late-planting-season update is given by $\varepsilon^{\text{late}}$, the difference between the final shortfall and the March shortfall forecast. Positive updates mean that surface water scarcity became worse. I choose different baselines and shortfall updates in the appendix.

I will use the variation in the baseline shortfall forecast and shortfall updates across the ~ 200 water districts in my data to estimate how districts respond to shocks to surface water availability learned at different points in the planting season. Figure 4 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 the shortfall is positive, which is bad surface water news. The news across 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

[14]Recall that forecasts prior to February are extremely unreliable anyway

Figure 4: 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 mid-seniority State Water Project contract, the south-of-delta Central Valley Project contract, and the stronger 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.

water allocations evolve throughout the year.

My main econometric model is shown in equation 1. A_{dt} is the level of an adaptation action, for example land fallowing, observed in the dry season in district d in year t, given the baseline shortfall forecast and two shortfall updates. Intuitively, each coefficient of interest, β_1, β_2 and β_3, reflects approximately the percent change in the district's number of acres fallowed. The difference in the coefficients reflects if a different amount of fallowing can be attributed to a marginal shortfall shock from a different time in the planting season. By using district and year fixed effects, I compare a water district's adaptation choices to itself over time, which is the best comparison available. I will identify the effect of information on adaptation levels if there are no unobserved factors varying at the district-year level affecting both deviations in information and deviations in adaptation. I next describe each piece of the estimating equation in detail.

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

I study five water conserving and groundwater intensifying 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). The second is the level the depth to the groundwater table, a proxy for groundwater extraction, since the βs can be interpreted as a change in depth with a change in information. The third is land fallowing, so that A_{dt} is the number of idled acres in a district observed during the peak harvest time. In the another set of regressions, A_{dt} is the number of acres at peak harvest in other crop groups: low-water annuals, high-water annuals and perennials[15]. Finally, I also use district-level average evapotranspiration across the planting and dry season to proxy for changes in total water application. Since A_{dt} is bounded below by zero, and

[15]Since Poisson regressions are not typical in the crop-choice literature, I check the robustness of my Poisson results using a simple multinomial logit crop choice model, following Kurukulasuriya and Mendelsohn (2008).

zeros reflect a meaningful choice, I estimate the model using PPML[16] (Silva and Tenreyro, 2006). Poisson regressions naturally represent the aggregation of individual binary choices (Cameron and Trivedi, 2013).

X_{dt} is a set of district-year specific controls that control for endogeneity between the forecasts and the adaptation choice. There are three 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.

For some analyses, alternative adaptation decisions might pose a source of endogeneity. Because adaptation decisions might be substitutes or complements, each A_{dt} modelled by equation (1) is one of several simultaneous equations. Consider the choices of crop fallowing and groundwater extraction. If crop fallowing is the dependent variable, and I control for groundwater extraction, each β isolates the direct effect of surface water shortfalls on crop fallowing. If I fail to control for groundwater extraction, then β also captures how shortfall increased groundwater extraction, and then how groundwater extraction changed fallowing. In my analysis, I actually do not want to control for these mechanisms because they reflect part of the adaptation response. However, I compare the main results with those controlling for alternate adaptation decisions using the control function approach (Imbens and Newey, 2009). I describe the methods and results in Appendix B.1.

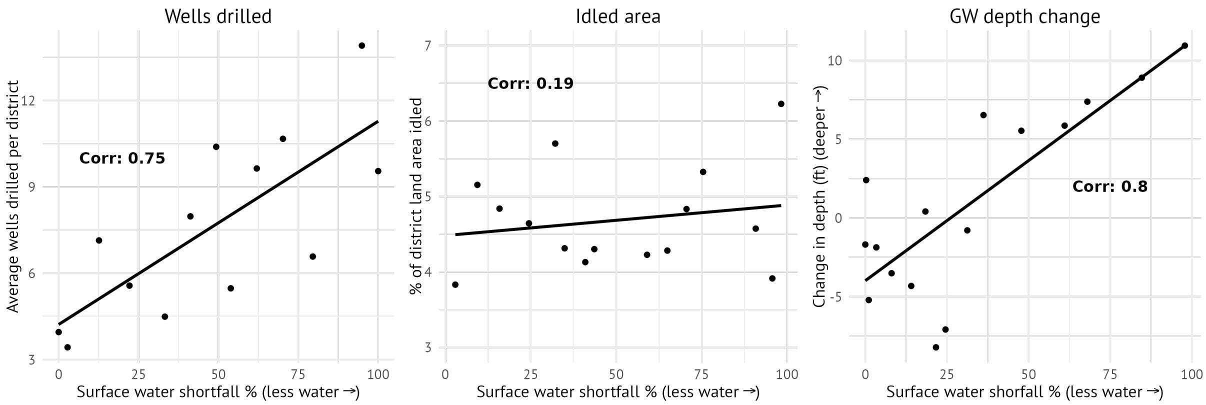
Finally, ν_{dt} is the error term. In my main specifications, I cluster standard errors at the contract level, designating each district with a different pattern of surface water forecasts as having a different contract. Therefore, I have 35 contracts in my dataset. In other forecasting papers, the treatment (weather) is not applied to a specific location, so spatial-correlation-robust standard errors 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.

3.2 Results

I motivate my main results by showing that in the raw data, farmers act decisively in years with high surface water shortfalls. Figure 5 shows a simple raw-data binscatter of wells drilled, idled land and the change in depth to the groundwater table on the final surface water shortfall percent. The raw data relationships are displayed in figure 5. Higher shortfalls correlate strongly with higher uptake of each of the farm adaptation

[16] The shape of the ET variable also makes OLS a reasonable choice. I use OLS in the appendix for reference.

Figure 5: Raw data binscatter: adaptation actions on final surface water shortfalls



Note: On all plots, the x axes reflect shortfall, a lower surface water allocation. 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.

options. The main empirical specification will confirm that these patterns are causal, and also reveal when in the season farmers make different decisions.

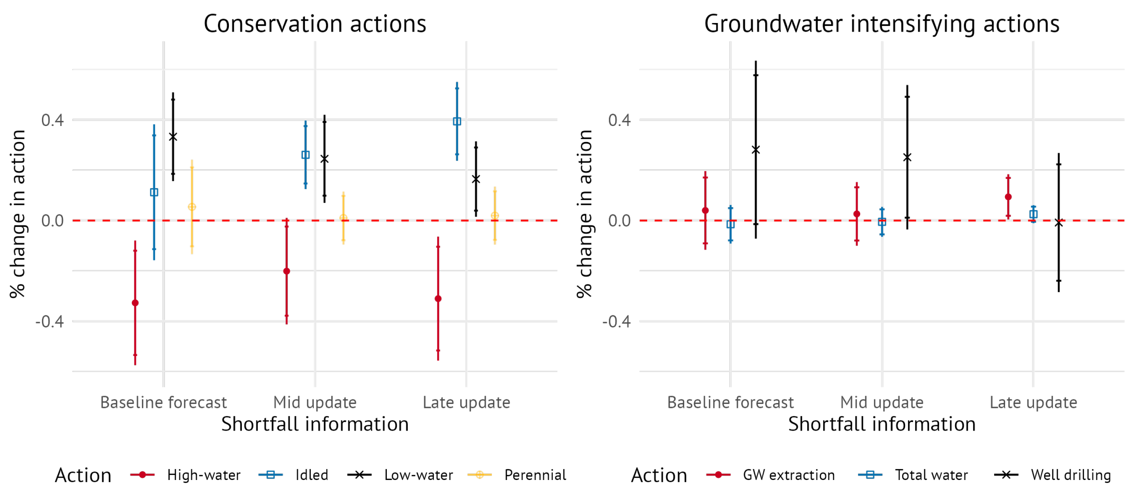
In figure 6, I show the causal effect of an increase in shortfall announced in the early, mid, and late planting season on seven different adaptation actions. I plot three coefficients for each action, corresponding to the β coefficients in equation 1. The coefficient represents the percent change in an action observed during the dry season resulting from a one-point increase in announced shortfall in a particular period. The coefficients are organized by shortfall announcement timing, either the baseline forecast, the mid-planting season shortfall update, or the late planting season shortfall update. The numerical results are in Appendix B.2. 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.

The left panel displays the results for the water-conserving choices, specifically, crop selection decisions. Low-water annuals are denoted by black x's, high water annuals by red dots, idled acreage by blue boxes and perennial acreage by yellow diamonds. A positive coefficient means that a one-point increase in shortfall led to an increase in planted acreage in a particular category. I find that a one-point increase in shortfall in any period of the year leads to an average of a .27% increase in idled acreage, a 0.23% increase in low-water acreage, a 0.26% increase in high-water acreage, and a 0.03% increase in perennial acreage, a shift in about 25 acres for the average district.

The right panel shows the response of groundwater intensifying actions to surface water allocation shortfall, which are the percent changed in wells drilled (black x's), groundwater extraction (red dots), proxied by the increase in depth to the groundwater table, and the change in total water applied (blue boxes), proxied with evapotranspiration. A one point increase in shortfall results in a 0.18% increase in well drilling on average, a 0.01% increase in total water applied, and a 0.04% increase in groundwater extraction, about 2 new wells across all districts, a decline in the water table by about half-an-inch, and an increase in water application by 1/80 of an inch.

The general trends results are consistent with the raw data plots from figure 5. In response to surface water shortfall, farmers take both water conserving and groundwater intensifying actions. All of the crop choices

Figure 6: 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 (1), 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 dependent variable listed in the legend is one PPML regression. 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 contract level.

indicate farmers adjust their crop acreage in response to expected surface water availability. Farmers plant fewer high-water crops, and increase low-water crops and fallowing. However, farmers' average adjustment to their perennial acreage is only about 15% the size of the other responses, and is the only statistically insignificant response. The response makes intuitive sense: the opportunity cost of abandoning perennial acreage is high. In contrast, farmers do respond through the other long-term investment choice, well drilling. The major question raised by this result is about the additionality of these wells. Are farmers adapting by drilling wells a few years early, or drilling wells they never would have otherwise? I answer this question in section 4.

My results also reflect important patterns in adaptation across the planting season, especially for groundwater intensifying actions. Farmers only drill wells in response to early changes in information, and they only extract additional groundwater in response to last-minute surprises in surface water shortages. For conservation actions, most coefficients remain statistically significant throughout the growing season, showing that farmers continue to adapt with crop choice as they receive new information, although the crop idling response may be larger in response to information at the end of the planting season.

These results paint a broad picture of the way that farmers in California are adapting in aggregate to short-run surface water scarcity. Early in the planting season, farmers across the state especially take water conserving actions with lower private costs, like switching from high-water acreage to low water acreage. These choices keep water use nearly the same, meaning that on average, farmers almost fully substitute their surface water shortfall with additional groundwater, supported by the positive (though insignificant) coefficient on groundwater extraction. Therefore, either within or across districts, farmers take a mixed conservation-groundwater substitution strategy early in the season. At the same time, farmers drill wells.

For well drilling, there is a yearly tension between the option value of delaying drilling until the final surface water shortfall is certain, and the short-term gain of being able to use groundwater in the current year. The results show that the latter mechanism dominates in year-to-year adaptation.

Late in the planting season, farmers respond differently to shortfall shocks. When water becomes scarce right before the dry season, groundwater extraction increases at more than twice the rate observed earlier in the season. In fact, on average farmers over-adapt to surface water shortfall, evidenced by the overall increase in total water application. Something about late-season surface water shocks increases the value of every unit of water, shifting out the marginal benefit curve. One possible explanation is that earlier investments were tailored to specific conditions. For example, a farmer might plant tomatoes in wet years and wheat in dry years. Getting a late surface water shock conditional on having planted wheat raises groundwater use to offset lost surface water. However, conditional on having planted tomatoes, the farmer will need to use much more water because tomatoes are sensitive to water stress, and the farmer no longer has options to adjust any other inputs. Despite the increases in total water application, farmers continue to conserve water especially through land idling, suggesting that water requirements greatly increase under announcements of late-season water stress.

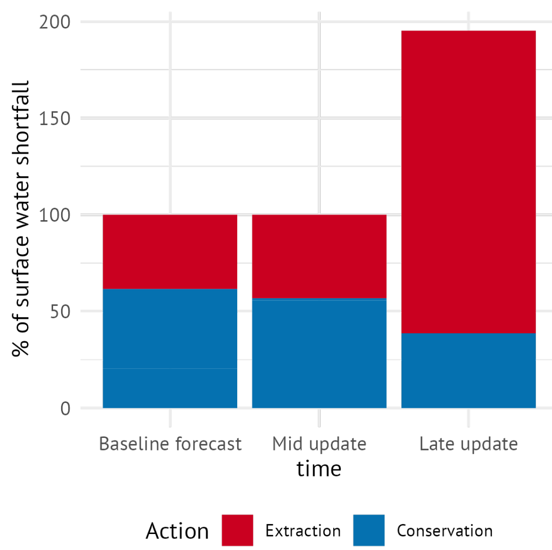
Understanding farmers' adaptation strategies is crucial because they compensate for lost surface water, which has defined property rights, by pumping groundwater, which imposes external costs on others. Equation (2) demonstrates how my estimates can determine what proportion of lost surface water farmers replace through conservation versus groundwater substitution. The framework is straightforward: the total change in applied water equals the change in surface water supply (due to the shock) plus the change in groundwater use. Using observed data, I can estimate how much the surface water allocation changes in each period following a shock. The second row of the equation explains that the gap between increased groundwater pumping and decreased surface water represents either conservation or additional water applied beyond baseline levels. I observe part of the conservation response through crop switching and land fallowing. I connect actions with changes in water use by making assumptions about water saved[17]. The residual is composed of unobserved conservation (a negative component) and excess water application (a positive component). For my back-of-the-envelope estimation, I assume one component is zero.

$$\begin{aligned} \Delta\text{Total water applied} &= \Delta\text{Groundwater extraction} + \Delta\text{Change in surface water allocation} \\ &= \Delta\text{Observed conservation} + \Delta\text{Unobserved Conservation} + \Delta\text{Excess water applied} \end{aligned} \tag{2}$$

In figure 7 I summarize how farmers make up for the lost surface water allocations on average across the state. The blue portions of the bar chart reflect water saved through observed and unobserved conservation actions, while the red bars show groundwater use. In periods where water application does not increase, farmers replace 100% of the shortfall using one of the two actions. A bar higher than 100% shows that farmers take adaptation actions to more than offset the surface water shortfall.

[17] In particular, 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.

Figure 7: Percent of surface water shortfall shock replaced by each type of action



Note: This figure shows the back-of-the envelope calculations for the percent of a surface water shortfall made up with either conservation (observed through fallowing and crop switching, plus unobserved through the residual), or groundwater extraction. To calculate these percentages, I use the estimates from 6, combined with the relationship in equation (2). The y-axis shows the percent of a surface water shortfall replaced with a particular adaptation practice. I omit any change in groundwater from new wells.

Early on, conservation dominates water use changes. More than half of lost surface water is offset through water-saving measures, both observed (idling fields and switching to low-water crops) and unobserved (shifting planting times, purchasing surface water on the market, storing precipitation, selecting different crop varieties and implementing soil management practices)[18]. As the season advances, however, farmers increasingly turn to groundwater. By the end of the planting season, groundwater substitution becomes three times more prevalent than at the start, making it the dominant adaptation strategy when late-season shortages occur.

Therefore, especially late-season conservation results in large increases in groundwater use. Through my calculation, I estimate that the average surface water shortfall shock is about 160 acre feet of surface water, consistent with 1% of a typical delivery from the data. After a late-season shortfall shock, a typical district would use 235 acre-feet more groundwater, enough to supply 500 households for a year. Scaling up to the entire Central Valley Project, which delivers 5 million acre-feet to farms annually, farmers would substitute to 78,000 acre feet more groundwater, or 0.8% of annual groundwater use in California.

This subsection gave a broad picture of agricultural adaptation: farmers adapt with many types of actions, and their choices change depending on when they get new shortfall information in a year. Although conservation is an important part of adaptation, farmers drastically increase groundwater use following late-season shortfall shocks. However, my main specification misses two parts of the story in characterizing adaptation. First, I take water districts as a homogeneous group. Likely, different types of farmers take the different adaptation actions I study. Second, I miss how patterns of adaptation change over time, especially

[18]Not shown in the plot, my estimates suggest unobserved conservation accounts for roughly 36% of total conservation early in the season, though this share declines as the year progresses.

as farmers make more investments in wells. The remainder of my analysis on how farmers adapt tackle these questions. First, though, I turn to a brief discussion in the robustness of the main result.

3.3 Robustness checks

My adaptation results are robust to a variety of alternate specifications. Appendix Section B.2 presents five robustness tests for each of the seven adaptation choices. First, I omit all controls. This specification reduces the statistical significance of groundwater intensifying actions, especially groundwater extraction, though coefficient magnitudes and directions remain unchanged. I find that controlling for neighbors' extraction is important for statistical significance. Second, I add a control function for alternative adaptation choices to the main specification, effectively shutting down substitution and complementarity channels. The magnitudes of groundwater-intensifying actions increase slightly, though not significantly, consistent with the intuition that holding crop choice fixed would increase groundwater intensification. Third, I use Conley standard errors to account for spatial correlation within 100 kilometers (slightly larger than the average California county). Conley errors generally strengthen my results: most coefficients become more significant or retain similar significance levels. The one exception is the late-season low-water crop response, which loses statistical significance. However, since low-water crops tend to be planted early, Conley errors actually move my results closer to my ex-ante expectations. Fourth, I use January shortfall forecasts as the baseline for surface water information rather than the previous year's shortfall. I fill missing early forecasts with the nearest forecast (in space). The exception is high-water crop responses which become statistically significant only in the earliest period, and well drilling responses which become statistically significant only in the mid-update period. Neither result changes my story, though better early-planting season data might have revealed more interesting patterns. Fifth, I estimate the model using OLS rather than PPML. OLS is inappropriate for most adaptation choices, especially well drilling. Histograms in Appendix figure B.3 shows that fitting count data (wells) and skewed data (groundwater depth) with OLS results simultaneously in too many points being very well fit and very badly fit. Consequently, most OLS results are statistically insignificant. For dependent variables better suited to OLS (evapotranspiration and crop idling), the OLS coefficients match the PPML signs.

Finally, I estimate crop choice using multinomial logit (Appendix Section B.3), with perennial acreage as the omitted category since permanent crops are insensitive to short-run scarcity shocks. The log-odds from multinomial logit align in direction with my main specification, confirming that my crop results are not driven by the unconventional choice of Poisson estimation.

3.4 Heterogeneity by the well stock, district location, and shock direction

I conclude this section with three heterogeneity analyses to fill in the picture about how farmers adapt. In the first two tests, I see how farmers' adaptation decisions differ if they are in water districts with more wells, or in different locations. These tests answer whether different farmers might choose different adaptation methods, which helps to clarify the interpretation of the main result. The last heterogeneity test examines whether farmers respond differently to positive and negative shortfall shocks. Currently, I estimate the effect of a linear shock on adaptation, which implies that good surface water shocks would lower groundwater use as much as bad shocks raise groundwater use. If the effect is not linear, however, external costs do not net out over time.

I first examine adaptation in districts with different amounts of wells. Districts with more wells not only have the option to extract more groundwater, but wells also lower the value of conservation. Groundwater acts as a backstop resource during dry years, when surface water prices increase much faster than groundwater costs. When a farmer gets access to groundwater, her costs saved through conservation decreases. To test the heterogeneous response, I interact the three components of surface water shortfall from equation (1) with an indicator for a district being in the second or third tercile for wells-per-area. I allow a district's category to change over time so that I can compare districts to themselves because there is selection across space. In table 1 I show the results for three adaptation responses: groundwater extraction, total water application, and crop idling.

The first three rows show the adaptation responses for districts with the lowest number of wells in a given area. The baseline category tends to include older years (with a median year of 1995 versus 1998) and tends to include more districts in temperate agricultural areas. Overall, conservation responses are stronger than in the main specification. Total water applied significantly decreases with shortfalls, and the idling response is strong.

The next six rows compare the baseline results with district-years in the second and third terciles of wells. The wells-tercile category compares many districts to themselves – almost 2/3rds of districts change wells terciles. Farmers in districts with more wells conserve less water. These districts increase their water application relative to low-wells districts, so that total water application remains roughly constant with and without surface water shortfall shocks. The idling response also disappears for districts with the highest number of wells.

Overall, I find that districts with the most wells and districts with the fewest wells adapt in nearly opposite ways. This means the overall adaptation patterns shown in my previous results don't represent what a typical district does. Instead, they reflect an average across districts that are actually behaving quite differently from each other. This is the first evidence in my paper that long-term decisions shape short-term adaptation patterns. Because wells are permanent, each well-drilling decision likely pushes farmers toward relying more heavily on groundwater over time. I explore this long-term shift in greater detail in the next section.

In the next heterogeneity test, I study how adaptation differs across regions in the state. In California, groundwater availability and planting dates vary considerably across the state. In appendix figure A.6 I show a map aggregating ecological regions into 3 large regions with similar planting times and groundwater access. Planting times matter because a March 1st surface water forecast might be relatively early for some districts, and late for others. The South and Central Coast includes districts along the Pacific Coast and in the rainier area between the Sierra Nevada and Central Valley. The weather in these regions tend to be cooler, meaning that planting times are later. These regions also have some important groundwater basins, though they tend to be smaller and have better governance. The Central Valley has a deep aquifer and a long agricultural season spanning most of the year. The Inland Desert regions tend to plant early and have minimal groundwater access, therefore relying heavily on surface water. To study heterogeneity across regions, I let the temperate South and Central Coast be the baseline, and compare adaptation actions in the Central Valley and Inland Desert by interacting the three components of surface water shortfall from equation (1) with an indicator for a district being in either region.

I show the results in Appendix Table B.9. Overall, districts in the temperate region in the state adapt less than the average district. In contrast, the majority of the groundwater extraction effect comes from

Table 1: Adaptation by number of wells

	Extraction	Total Water	Idling
Baseline shortfall	-0.07	-0.11^{**}	0.20
	(0.11)	(0.05)	(0.28)
Mid-season shortfall update	-0.06	-0.19^{***}	0.38^{***}
	(0.08)	(0.06)	(0.15)
Late-season shortfall update	0.03	0.03	0.44^{***}
	(0.09)	(0.02)	(0.12)
Baseline × Mid wells	0.19	0.13^{***}	0.17
	(0.11)	(0.03)	(0.25)
Baseline × High wells	0.07	0.14^{***}	-0.32
	(0.12)	(0.03)	(0.25)
Mid update × Mid wells	0.12^{*}	0.23^{***}	0.05
	(0.07)	(0.04)	(0.17)
Mid update × High wells	0.07	0.22^{***}	-0.43^{*}
	(0.07)	(0.06)	(0.22)
Late update × Mid wells	0.10	-0.02	0.01
	(0.08)	(0.02)	(0.15)
Late update × High wells	0.03	0.04	-0.37^{**}
	(0.08)	(0.03)	(0.15)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall components by the wells-per-area tercile of a district, which can change over time. The baseline category in the first three rows are the districts with the fewest wells. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

the Central Valley, the region with the least regulated and most abundant groundwater, and also the most perennial acreage. I do not find convincing evidence that different regions respond to information in different times. Desert regions might start responding to shortfall shocks by idling earlier, though the other patterns show mixed results.

In the final heterogeneity test, I examine whether farmers have different adaptation responses to good and bad news about surface water shortfall. I interact the two shortfall updates with an indicator for whether the update was positive (bad news). Since positive updates are rare, I also define a 0-shortfall decrease as bad news, given a bad initial forecast (greater than 40%) since the shortfall forecast nearly always declines across the planting season. I show the results in Appendix table B.10.

Farmers exhibit a pronounced asymmetry in their responses to water availability shocks: they adapt far more aggressively to positive shortfall news (bad news) than they scale back adaptation when conditions improve. This pattern is particularly evident in water application decisions, which respond only to late-season announcements of increased shortfall. The asymmetry extends to groundwater extraction, where bad news triggers a response nearly four times larger than good news (though statistical significance on the interacted term is marginal, $p = 0.12$). Land idling decisions show a similar pattern, more than doubling in response to negative shocks. Therefore, adaptation to shocks lead to increased groundwater use and idling from the no-shocks baseline over time.

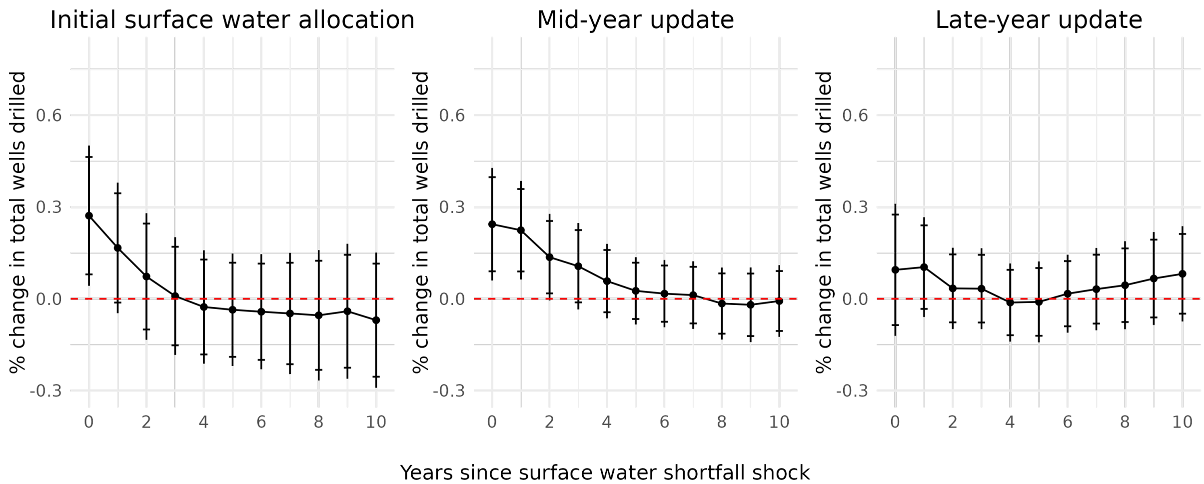
The whole of section 3 has pointed to potentially large external costs of adaptation to especially late-season surface water shortfall shocks. Farmers adapt especially with groundwater extraction. Further, extraction is highest and conservation is lowest in districts with more wells. Short-term shocks are driving up the stock of wells over time. Increased extraction in surprisingly dry years is not countered by decreased extraction in surprisingly wet years.

Well drilling is the major determinant of adaptation choices. However, the previous section did not explore why some districts drill well, nor what particularly (causally) changes in districts after drilling. Therefore, to complete the picture of agricultural adaptation, I next study the transformation of adaptation over time through well drilling.

4 Well drilling: agricultural adaptation in the presence of an unregulated resource

The main question I ask in this section is whether farmers drill wells in response to long term changes in surface water availability. Although section 3 showed that a short-term surface water allocation shock can shift wells forward in time, it is not ex-ante obvious whether a long-run change in surface water availability increases the value of wells on average in the long run since groundwater tends to be more expensive than surface water. Then, I turn to the consequences of well drilling, which I study in three parts. First, I examine how making well investments affects short-term adaptation choices, by estimating how a district's well stock affects the sensitivity of adaptation actions to short-term shortfall shocks. Afterward, I explore how drilling wells affect longer-run water use decisions on farms. I first see how new wells increase district groundwater use in normal water years. Then, I finish the section by studying how exogenous new wells affect farmers' crop choices over time.

Figure 8: 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.

4.1 How do short run shocks affect the longer-run stock of wells?

Section 3 showed that some wells are drilled because of short-run shocks. A short-run shock is a small shift in the surface water supply that nudges some farmers with a well value near the threshold of drilling to drill. As well values in California are rising over time, these short run shocks contribute to earlier long-run adaptation over my period. This subsection traces the dynamic impact of a one-time surface water shortfall shock on the stock of wells in a district. Through this analysis I learn how much earlier wells are drilled than they would have been otherwise, which allows me to quantify the longer-term social costs of adaptation to short-run surface water supply shocks.

I estimate the dynamic effect of the short-run shortfall shock using local projections (Jordà, 2005). Local projections will estimate the impulse response of a surface water shortfall shock in year t on the cumulative stock of wells in a water district over horizons $h = 0, 1, ..., H$ (i.e., from year t through year $t + H$), relative to the pre-shock baseline. The key identification assumption is that surface water shortfall shocks are exogenous conditional on past information, meaning the shock in t is not affected by contemporaneous well-drilling decisions (Jordà, 2023). The estimating equation is similar to equation (1), where the major difference is that the dependent variable is the sum of wells drilled in a district from year t 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). I then run $H = 10$ separate regressions.

I plot the effect of the shortfall shock over time in figure 8. Each plot shows the path of coefficients for one of the three shortfall components, and the points are the coefficient estimates for each of the time horizons, $h = 0, 1, ..., H$. The first point, for $h = 0$, corresponds to the year the surface water shortfall shock occurred, and is hence virtually the same as the short-term adaptation effect from figure 6[19]. For the information that well drilling responded significantly to, the initial surface water allocation and mid-year

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

update, the same trend appears. The effect of a surface water shortfall shock on the cumulative number of wells in a district decreases monotonically after the shock occurs, and levels off at no effect. Therefore, the wells drilled in response to the surface water shortfall shocks would have been drilled only a few years in the future. About half of the wells drilled in response to initial surface water would have been drilled the next year. For wells drilled in response to a shock in at the mid-year update time, about half would have been drilled within three years.

Despite the short-run effect lasting for a short time, there is still a real social cost to drilling wells early. Groundwater will be extracted earlier, and farms will adjust other inputs earlier. Therefore, society bears the costs of externalities from extraction starting this year rather than several years from now. Also, stored groundwater is more socially valuable than the marginal extracted groundwater unit because of the scarcity rents that can be collected under future regulation. Extracting too early lowers long-term welfare.

The dynamic analysis showed that small shortfall shocks shift some wells forward in time. When I calculate the costs of adaptation to short-run shocks in the final section of the paper, I need to account for the additional water used in each of the periods that districts had more wells than their counterfactual trend. Combined with the general well drilling trend from figure **??**, we learn that these small shocks play a continual role in the long-term adaptation story, shifting the farmers with the highest well values to drill earlier.

4.2 Do farmers drill wells as a long-term adaptation strategy?

Separating the study of short and long-term surface water supply on well drilling is tightly connected to new advancements in the climate econometrics literature. Deschênes and Greenstone (2007) showed using the envelope theorem that the effect of deviations in local weather from the average on economic outcomes identify the effect of climate. However, Lemoine (2018) clarifies the theory primarily by showing that capital and resource-intensive adaptation makes the effect of short-term weather fluctuations differ from the effect of long-term climate. My paper will explore whether the theoretical advancement has practical implications in California agriculture.

Lemoine (2018) lays out reasons for why agents might adapt differently in the long-term than the short term. First, agents might only pay for long-term investments if the climate permanently changed. Second, a change in short-run forecasts is different from a permanent change in expected weather. Third, reactions to short-run weather and long-term climate are different. Equation (3) formalizes how short-term surface water scarcity and long-term surface water availability factor in to a simple well drilling choice problem faced by the average farmer:

$$\begin{aligned} V(well=0,\hat{s},\bar{s}) = \max_{well\in\{0,1\}} \{ & \mathbb{E}(\pi(\hat{s}, well=0) + \beta\mathbb{E}(V(well=0,\bar{s},\bar{s}), \\ & \mathbb{E}(\pi(\hat{s}, well=1) + \underbrace{\beta\mathbb{E}(V(well=1,\bar{s},\bar{s})}_{\text{stopping value}} \} \end{aligned} \tag{3}$$

The well choice value function V is made up of three inputs, whether the well has been drilled yet ($well \in \{0,1\}$), the current year's forecasted shortfall $\hat{s}$ and the expectation of the future average shortfall $\bar{s}$. In future periods, the forecasted shortfall is just the average expected shortfall. The farmer makes the choice to drill a well when the value of drilling now is greater than the value of waiting.

By studying the effect of short term shortfall on wells in section 3, I was targetting the first part of the value function, the current year profit: $\pi(\hat{s}, well)$. I found that changing $\hat{s}$ did not result in a permanent increase in wells, suggesting that $\hat{s}$ does not contribute very much to beliefs about $\bar{s}$. In this section, I target how a change in $\bar{s}$ affects the decision.

The main reason the climate econometrics literature exists is because it is difficult to find identifying variation from differences in climate, and it is analogously more difficult to identify adaptation to long-run surface water availability. Hagerty (2022) has one of the only papers studying long-run adaptation using quasi-random variation in long-run conditions. His paper also studies water scarcity in California, using a regression discontinuity across water districts with different quantities of water rights. Instead, I use a change in surface water allocation policy which applied only to water districts with project rights.

In October 1992, the US Congress passed the Central Valley Project Improvement Act, which redistributed 800,000 acre feet, about 14% of CVP water, of water from contractors to environmental uses. The act was highly controversial, and marked a fundamental and permanent change in the operation and goals of the Central Valley Project. The State Water Project was also affected due to the coordinated operations of the projects (McClurg and Sudman, 2000). the state had very little ability to curtail forms of water rights at the time, and thus no other rights were affected. Pressure for a law to protect the environment in the Sacramento-San Joaquin delta had been mounting since 1978, when the State Water Board issues Water Rights Decision 1485 requiring SWP and CVP to meet Delta water quality standards. However, no significant legislation had been passed, and no proposal had met either the State Water Board nor the EPA's requirements (Water Education Foundation, 2025).

I use the passage of the Central Valley Project Improvement Act to identify the effect of a permanent decrease in surface water for districts with project contracts. Since no surface water market existed at the time, only the project districts were affected. Districts with other forms of water rights make up the control group. I use a differences-in-differences type of event study design to estimate how districts facing the permanent decrease in surface water drilled wells compared to the rest. Equation (4) shows the estimating strategy:

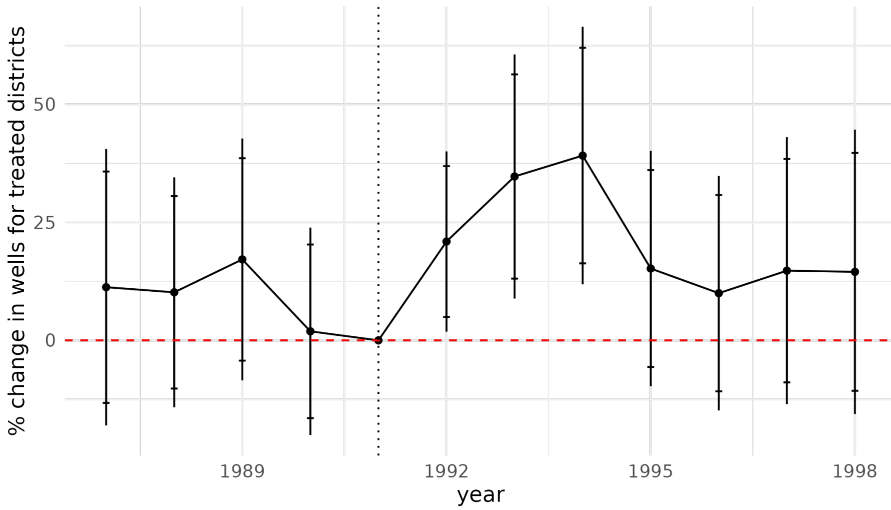
$$A_{dt} = \exp\Big(\sum_{y \in \{1987,\ldots,1998\}} \beta_y P_d \times \mathbb{1}(t = y) + X_{dt} + \gamma_d + \gamma_t + \nu_{dt}\Big) \tag{4}$$

P_d is an indicator variable for districts with project contracts. $\mathbb{1}(t = y)$ is an indicator variable for the year being equal to y, since the event occurs at the same time for all districts. β_y is the difference in the level of well drilling for project and non-project districts in year t. For my main specification, I continue to use a PPML regression since it best captures the well drilling decision. In robustness checks, I instead use (Callaway and Sant'Anna, 2021) to address any potential problems doing differences-in-differences with multiple periods, using a logged dependent variable.

Figure 9 shows the result. The baseline year is 1991, the year before the Central Valley Project Improvement Act was passed. In 1992, project districts drilled 25% more wells than they would have absent the act. In 1993 and 1994, project districts drilled nearly 40% more wells than otherwise. By 1995 and beyond, the treatment effect drops, and is not statistically different from zero.

Unlike the short-term drilling result, the number of wells drilled in response to the permanent shift in surface water availability is not temporary. Six years after the shock, there is no evidence in the well drilling trend reversing to capture wells that would have been drilled several years in the future. Also, compared

Figure 9: Wells drilled in project relative to non-project districts after CVP Improvement Act



to the short-term results, the amount of well drilling increase is huge. Officially, 14% of CVP water was reallocated to environmental uses. Empirically, I find that post 1992, districts' allocation was on average 13 percentage points less, after accounting for a time trend. Therefore, the treatment in the event study was 14 times larger every year than the marginal shortfall change I explored in section 3, but the well drilling effect was 350 times larger, and permanent.

4.3 How much does groundwater use increase after well drilling?

We expect well drilling to increase groundwater use. However, there are several details that are not obvious. First, we do not know ex ante whether farmers use groundwater in years with a normal allocation of surface water. Since groundwater tends to be more expensive in normal surface water years, farmers would use groundwater if districts set the price of surface water lower than the marginal product of water (given that the water district usually imposes limits on the quantity of surface water that can be purchased). Second, there is the fundamental unknown in water management in California: how much water do farmers extract from a given well? In this section, I regress depth to the groundwater table over time on new wells drilled in a particular year. I explore the dynamic path using local projections with instrumental variables.

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). The independent variable of interest is the projected number of new wells in a county, and the dependent variable of interest is the level change in acreage in a particular crop j between year t to $t+h$. In the local projections framework, the standard IV exogeneity requirement requires that the instrument should only be correlated with the contemporaneous shock and not with leads or lags of the shock (Stock and Watson, 2018). Including lagged well drilling as controls helps address potential violations of this assumption by accounting for the predictable component of drilling activity.

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 an instrument to capture well drilling decisions unaffected by current water conditions. I construct an instrument using the interaction of two variables that capture different well supply shocks. The first is a measure of market power in the well drilling market. Higher market power should increase the price of wells holding all else equal. In my main specification, I measure market power by counting the number of well drilling companies operating in the area. I specifically I take the 25 kilometer buffer around the convex hull of all wells drilled by a contractor over all time, where contractors are defined by an entity that drilled at least two wells, and the lifetime of the contractor is taken as the time period between its first and last well drilled. Not all contractors drill wells every year, so the variable captures the number of drillers capable of drilling in an area at a given time, while separating the variable directly from well demand. Further, the instrument is not directly connected to well demand since contractors cannot enter the market immediately due to certifications and machinery investments required. In robustness check, I alter the buffer, alter the definition of the time in business, and redefine market power using the Herfindahl-Hirschman Index (HHI) over the number of wells drilled in a particular year.

The number of contractors varies across space and time, though the spatial pattern of the number of contractors remains similar. Thus, I interact the market power variable with another variable affecting well supply: 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, and this variable exists across most of my analysis. 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). Steel piping prices are definitely exogenous to the extraction decision except through wells drilled, making the instrument valid.

Equation (5) shows the first stage of my instrumental variables specification. Y_{dt} is the number of wells drilled between January and August. N_{dt} denotes the number of contractors, and P_t denotes the input prices. The excluded instrument is $N_{dt} \times P_t$. I include these as level variables because they are distributed close to normally in my data. I include all of the controls as in my previous estimation, X_{dt}, and the same fixed effects. The first stage estimates the well decision linearly, as required by the assumptions of two-stage least squares. There is no clear way to transform the dependent variable in my case. Many districts choose 0 wells in some t creating problems for interpreting a log transformation (Chen and Roth, 2024). I show the results of the first stage estimation in table 2.

$$Y_{dt} = \alpha_1 N_{dt} \times P_t + \alpha_2 N_{dt} + X_{dt} + \gamma_d + \gamma_t + \nu_{dt} \tag{5}$$

The first stage results show that the well supply variables empirically affect the number of wells in an intuitive way. The first column regresses the number of wells only on the well supply variables. Even without including fixed effects, the coefficients on the first two variables remain similar across all specifications, giving suggestive evidence that these variables are not determined by the drilling decision. In the raw data, a higher steel pipe price significantly negatively correlates with drilling. The second and third columns include the appropriate fixed effects. Overall, as the number of contractors increases in a district relative to the district's average and that year's average, the number of wells drilled increases. Therefore, adding more contractors appears to actually shift the well supply curve out. The direction on the coefficient of the actual instrument is not ex-ante obvious. It shows that as steel pipe prices rise, how an additional contractor contributes to the number of wells in a district. The positive coefficient means that during periods of high steel pipe prices, the number of contractors influences well drilling even more. Intuitively, increases in input prices matter less

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

	First stage			Reduced Form		
	(1)	(2)	(3)	(1)	(2)	(3)
Contractors × Steel pipe price ($100)	0.006***	0.004***	0.004***	0.063**	0.042***	0.043***
	(0.001)	(0.001)	(0.001)	(0.025)	(0.011)	(0.011)
Contractors	0.016***	0.016***	0.017***	0.056	0.128	0.127
	(0.004)	(0.004)	(0.004)	(0.098)	(0.082)	(0.087)
Steel pipe price ($100)	−0.637***			3.497		
	(0.143)			(4.540)		
Controls	no	no	yes	no	no	yes
District FEs	no	yes	yes	no	yes	yes
Year FEs	no	yes	yes	no	yes	yes
F-stat	132	132	127	NA	NA	NA
Num. obs.	4882	4882	4923	4882	4882	4882
Adj. R^2 (full model)	0.181	0.760	0.761	0.069	0.805	0.805

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

Note: The first three columns show the first stage for how the number of wells are affected by the instrument, and the last three columns show the reduced form for how the depth to the groundwater table is affected by the instrument. The instrument is the first row, the interaction of the number of contractors and the current steel pipe price. The other two variables are included in the regression. Each column adds stronger fixed effects or controls. (1) has no controls or fixed effects, meant for building intuition. (2) adds year and district fixed effects and (3) adds all of the controls.

in districts with more contractors, perhaps because the firms continue to compete in prices. The instrument is highly statistically significant across all specifications.

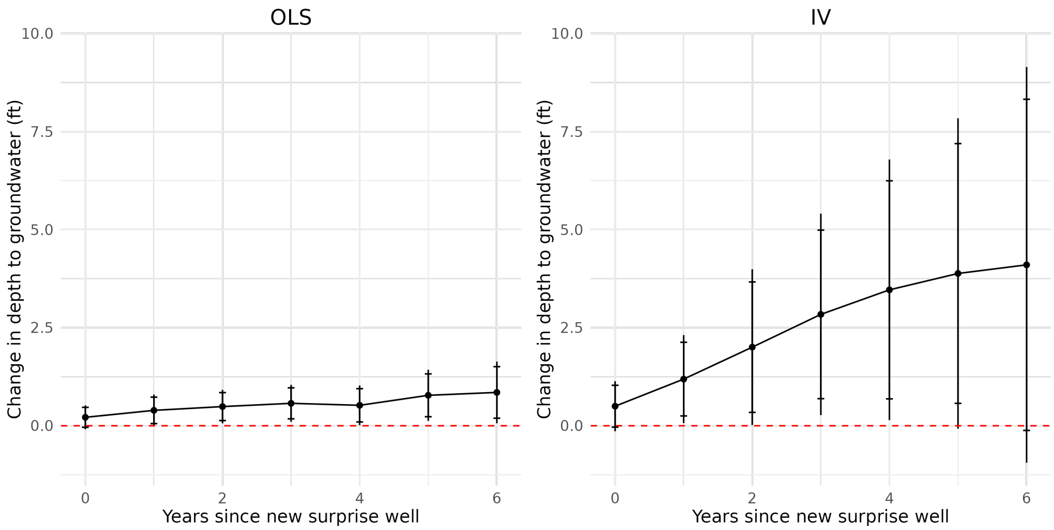
The instrument I propose induces a minor shift in the value of wells through the well cost. Therefore, the farmers affected are those with well values close to the threshold of drilling into drilling, and who might have drilled a few years in the future. These farmers are different from the rest of the population, who will not drill for several decades, who who had drilled several decades prior. Nevertheless, the local average treatment effect is interesting and relevant. The two-stage least squares results will capture changes in extraction for the farmers likeliest to drill next.

I then show how a new well affects the depth to the groundwater table within a local projections framework, and plot the results in figure 10. The left panel shows the cumulative change in depth to the groundwater table using OLS within each of the local projections regressions. The right panel uses instrumental variables. New agricultural wells lead to increases in depths to the water table, by 0.8 after 6 years in the OLS specification, and a little more than 4 feet after 6 years in the IV specification. It makes sense for the OLS estimate to be biased downward because across time, as districts have a higher well stock they drill less (as recently shown) but also would extract the most groundwater.

The IV estimate is quite high, averaged over a district. The USGS's theoretical estimates of groundwater drawdown from large agricultural wells predict that at a distance of 1 mile of the well, a moderately large agricultural well (1000 gallons per minute) would draw down the aquifer about 2 feet after 1 year, and the largest agricultural wells (4000 gallons per minute) would draw down the aquifer about 8 feet (Kunkel, 1960)[20]. The IV estimates are reasonable given the USGS theoretical estimates, if farmers are drilling large

[20]The USGS model also predicts that drawdown is higher close to the well; about 4 feet and 11 feet for the moderate and large wells at a distance of 1000 feet. Drawdown is also the fastest in the beginning. After 10 years, the drawdown of these

Figure 10: Change in depth to the groundwater table with 1 new well in a district



wells and extracting large quantities immediately. My estimates imply that about 1800 acre feet of water are extracted in the first year in the average district, which is approximately the capacity of a 1000 GPM well. Theoretical groundwater drawdown predicts a logarithmic change in depth to the groundwater table if groundwater is being extracted at a constant rate. The IV estimates show the expected levelling off over time, though the rate of change in the first four years is fairly linear, suggesting increasing extraction in the first few years.

This subsection reveals that farmers use new wells immediately and extensively. The local average treatment effect captures the effect of drilling a well in an average year, since the well supply shocks I use are not related to surface water supply. Yet, the instrumental variables estimates are consistent with farmers having drilled large agricultural wells, and extracting large quantities in the average year[21]. Thus, the marginal new well drillers do not merely supplement their surface water with groundwater, but rather greatly increases the water intensity of the farm.

4.4 How do farmers change cropping patterns after drilling?

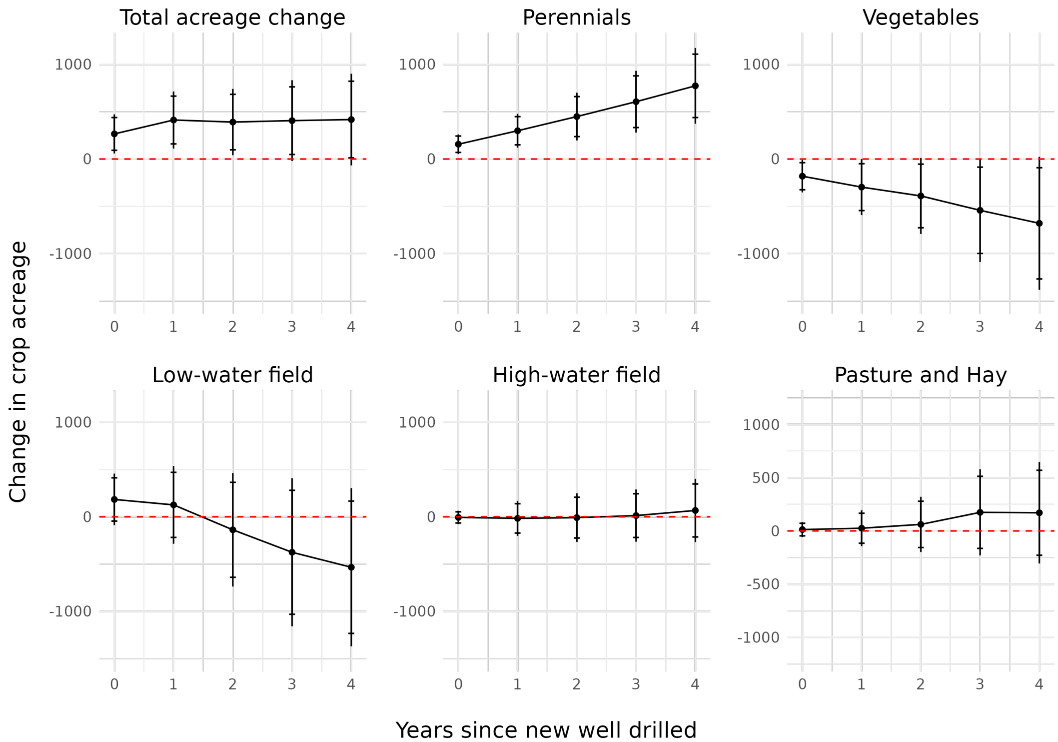
The previous analysis showed that farmers extract large amounts of groundwater from new wells, resulting in a persistent change in farm water use. There was also a suggestive pattern that farmers might be increasing their extraction over time. I finish my study of the effects of well drilling by exploring how drilling affects the water intensity of agriculture through 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.

Like in the previous analysis, I use local projections with instrumental variables. I need to study the crop decision dynamically because new wells change the value of planting different crops, but farmers often cannot switch immediately. Instrumental variables are required particularly because the value of crops

wells at 1 mile is about 3 feet and 11 feet respectively.

[21]The raw data shows that the proportion of the highest capacity wells (greater than 2000 GPM) increased from 5% to 15% of new wells drilled between 1990 and 2015.

Figure 11: 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).

directly determines the cropping choice, and the value of a well. The same instrument as the previous analysis is valid here since well supply shifters only affect cropping choices through making wells cheaper.

My original dataset will not allow me to study the dynamic effects of well drilling on cropping, however. The Cropland Data Layer is short, which leads to bias in local projections (Herbst and Johannsen, 2024). Therefore, I perform the main analysis on the longest panel of harvested cropland available for California, which spans from 1980 to 2022 from California's Agricultural Commissioner (CA Agricultural Commissioner, National Agricultural Statistics Service, 2025). I aggregate the same control variables used previously to the county level. Otherwise, the analysis proceeds in the same way.

Figure 11 shows the dynamic consequences of well drilling on acreage. Total acreage increases immediately after drilling, originating from an increase in perennials and (relatively) low-water field crops like grains and corn. The total acreage change stabilizes at around 450 acres, driven over time by increasing perennial acreage. Perennial acreage increases seemingly at the expense of vegetable acreage.

These cropping changes explain the groundwater extraction results from the previous subsection. I found that groundwater extraction increases immediately. Similarly, new wells result in an immediate increase in harvested acreage, where farms begin by planting low-valued, but low-labor (and therefore easier-to-plant) field crops. They then shift over time to the highest-water crop category, perennials. A large portion of the new perennial acreage comes from high-valued vegetable acreage. This shift is intuitive. Both crop types are high-valued, and require good soil quality, sunshine, and high amounts of labor for harvesting, making them potential substitutes for farms in certain locations in California. However, the shift across these crop types generally means an increased water requirement over time. During growing periods, these crops require similar quantities of water, though perennials need to be watered year-round. Perennials also have a higher opportunity cost of fallowing, meaning that many more farmers will opt to water perennials during dry spells. Thus, well drilling drove major changes in agricultural production within California.

4.5 Adaptation to surface water scarcity led to groundwater intensification in the long run

Section 4 showed how well drilling led to changes in short-run adaptation, and major increases in water used over time through an expansion of irrigated land and a shift toward higher-water intensity crops. The first two subsections showed how a portion of well drilling can be directly attributed to shocks to surface water availability.

5 Private value of adaptation to surface water scarcity

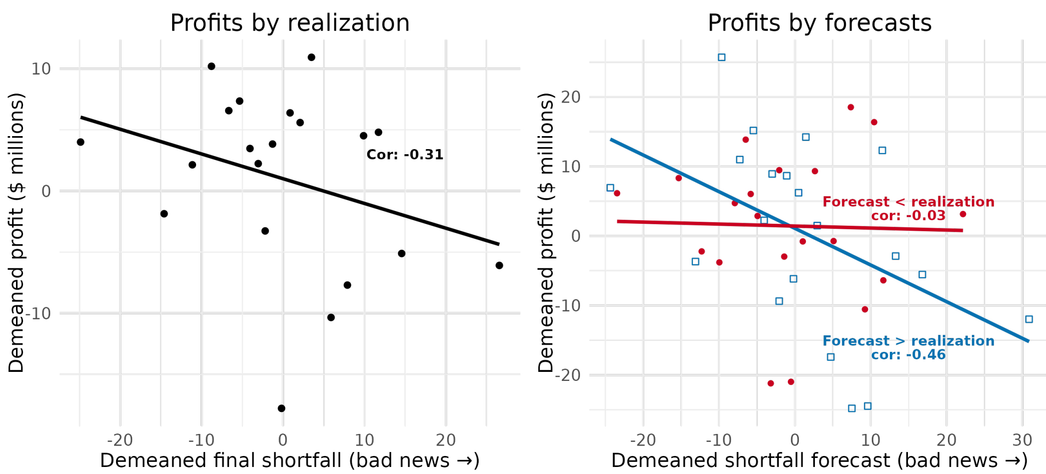
Surface water scarcity is bad for farms. The left panel in figure 12 shows that after controlling for county and year fixed effects, higher shortfalls correlate with lower profit[22]. The previous sections went into detail identifying how farmers take adaptation measures to avoid net profit losses. This section quantifies the value of all of the actions that farmers take in different periods throughout the year.

The net private benefit of adaptation comes from the profits that farmers are able to save through choosing appropriate actions for the level of surface water shortfall realized during the dry season. In agriculture, many of these actions, like crop choice, must be made well before the realization of the surface water shortfall. The benefit of adaptation therefore crucially depends on the accuracy of the surface water shortfall forecasts. The right panel in figure 12 illustrates this fact in the raw data. When the surface water shortfall forecast was higher than the realized shortfall, higher shortfall forecasts correlate with lower profits. Intuitively, a higher shortfall forecast is further away from the truth, and thus adaptation becomes less appropriate for the realized level of shortfall. On the other hand, when the forecasted shortfall was lower than the realization, the negative effects of higher shortfall forecasts disappear. In this case, a higher shortfall forecast results in adaptation better suited for the actual level of surface water.

I begin this section with a simplified conceptual framework that will give us an idea of how to estimate the value of adaptation to surface water scarcity. The main intuition is that value of the accuracy of the forecast is equivalent to the benefit of short-run adaptation. By capturing how much more profit farmers earn if the forecast was one point closer to the realization, we capture the value determined by the specific actions tailored to the level of the forecast that cannot be perfectly adjusted later. Afterward, I apply the framework to data and show the results. Valuing farmers' actions will allow us to understand the relative magnitude of the problem of the social costs of adaptation.

[22]The negative relationship between surface water shortfall depends on the unit and time controls, since log revenues and years have a correlation of 0.97, average shortfall and years have a correlation of 0.62, and average shortfall and average revenue have a correlation of 0.25. In appendix figure A.7, I show that the negative relationship between revenues and shortfall appears as soon as I at least control for a year trend and the average shortfall in a county.

Figure 12: Binscatters of county-level profits on the surface water shortfall, controlling for county and year fixed effects



Note: Both plots demean the level of profits by county and year fixed effects, after winsorizing profits at the 5% and 95% level. The left plot bins the demeaned final shortfall, and the right plot bins by the demeaned shortfall forecast, after grouping observations by whether the demeaned difference between the realization and the forecast was higher or lower than zero. This process embeds the assumption that farmers rationally update the forecasts to mean zero bias.

5.1 Conceptual framework

In this conceptual framework, I design a stylized model of current-year net benefit (profits) for a farmer, incorporating the sequential adaptation empirically observed in section 3. I then show how changing information at different periods in the growing season identifies the value of adaptation. I conclude by showing how to use the model to derive the benefit of adaptation empirically. This conceptual framework builds on Shrader (2023) by examining a context with multiple periods of adaptation within a year.

Farmers take adaptation choices throughout the year based on information available at a certain time in order to maximize a static profit function[23]. As I showed in section 3, farmers take different adaptation choices within a year, revealing that ex-post profits depend on the actions taken in several periods within a year, and that the actions in different periods are not perfectly substitutable. Therefore, I differentiate an abstract action a by the time in the year it is taken, $\{early, mid, late\}$. By the time that profits are realized, ex-ante adaptation a^*_{early} and mid-season adaptation a^*_{mid} are already determined; they are implicit functions of the information available at the time and previous adaptation. Ex-post adaptation a_{late} occurs right after the final shortfall is revealed. Let adaptation actions be increasing in surface water scarcity, so that $\frac{da_{early}}{d\hat{s}} > 0$.

The final profits also depend on the realized surface water shortfall directly, s, as is intuitive and reflected in figure 12. As defined throughout the paper, the final shortfall is made up of the shortfall forecast, and the two updates across the year: $\equiv \hat{s} + \varepsilon^{\text{mid}} + \varepsilon^{\text{late}}$. To simplify the framework, I assume that each component is independent. Thus, the realized profits for one year is given symbolically by:

[23]I abstract away from the dynamic adaptation choice in this simple framework. See the appendix in the future for the dynamic adaptation choices.

$$\max_{a_{late}} \quad \Pi(s, a^*_{early}, a^*_{mid}, a_{late})$$

The value of adaptation comes from the following experiment: imagine there are two identical farmers, with the same s. Then, for the first farmer, we change $\hat{s}$. Now, the first farmer both received a different forecast, and ends up with a marginally higher s. The farmers now likely have different profits by the end of the season. The first farmer's profit changed because $\hat{s}$ changed, which led to different actions (say, idling an extra field) early in the season, and also because the final shortfall is slightly higher. The first channel is the value of adaptation. The second channel is the direct effect of water scarcity. I show how marginally altering each piece of information allows us to identify three pieces of information: the value of ex-ante adaptation, the value of mid-season adaptation, and the direct effect of water scarcity.

First, I show how the net benefit for a farmer changes if we alter the initial shortfall forecast:

$$\frac{d\Pi}{d\hat{s}} : \underbrace{\frac{d\Pi(s)}{da^*_{early}} \frac{da^*_{early}}{d\hat{s}} + \frac{d\Pi(s)}{da^*_{mid}} \frac{da^*_{mid}}{da^*_{early}} \frac{da^*_{early}}{d\hat{s}}}_{\text{value of ex-ante adaptation}} + \underbrace{\frac{d\Pi(s)}{da^*_{mid}} \frac{da^*_{mid}}{d\hat{s}^{mid}}}_{\text{value of mid-season adaptation}} \underbrace{\frac{d\hat{s}^{mid}}{d\hat{s}}}_{1} + \underbrace{\frac{d\Pi(s)}{ds}}_{\text{direct effect}} \underbrace{\frac{ds}{d\hat{s}}}_{1} \tag{6}$$

The farmer's profit changes through four channels. The first two combine to make up the value of ex-ante adaptation. If we marginally changed $\hat{s}$, we would marginally change the early adaptation choice, and changing the early adaptation choice inherently changes the mid-season adaptation choice as well. The value of adaptation appears in the same way as it does in (Shrader, 2023). It is how the net benefits change as actions change. I recover an estimate of these benefits precisely because I observe profits after all choices have been made; given the later shortfall information, a^*_{early} and a^*_{mid} are not optimal, so the derivative of realized profit with respect to these terms is not zero. Changing $\hat{s}$ keeping all other shortfall components ε^{mid} and ε^{late} constant changes the later information, $\hat{s}^{mid}$ and s marginally, by definition. Thus, changing the early shortfall forecast changes mid-season adaptation through the change in mid-season information, and also directly impacts profits through changing shortfall. I could analogously alter either ε^{mid} or ε^{late}. I summarize the result:

$$\begin{aligned} \frac{d\Pi}{d\hat{s}} &: \quad \text{Value of ex-ante adaptation} + \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\ \frac{d\Pi}{d\varepsilon^{mid}} &: \quad \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\ \frac{d\Pi}{d\varepsilon^{late}} &: \quad \text{Direct effect of scarcity} \end{aligned} \tag{7}$$

Equation (7) translates simply into an empirical model. Each derivative can be estimated through a regression of profits on the shortfall component. If I include all three in the same regression, as shown in equation (8), I can separately identify each. The value of ex-ante adaptation is given by $\beta_1 - \beta_2$, the value of mid-season adaptation is given by $\beta_2 - \beta_3$ and the direct effect of water scarcity is given by β_3.

$$\Pi_i = \beta_1 \hat{s}_i + \beta_2 \varepsilon_i^{mid} + \beta_3 \varepsilon_i^{late} + \nu_i \tag{8}$$

Before estimating the empirical model, we need to think carefully about the sign of the value of adaptation. Of course, adaptation is valuable in expectation. However, it is not necessarily valuable after the realization. Consider a farmer who receives a surface water shortfall forecast of 100%. She expects to get no water, and therefore abandons all of her crops. However, suppose her realized shortfall is 0%. The realized value of her ripping up her fields was net negative. More generally, consider the first term in equation (6) $\frac{d\Pi(s)}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}}$. Assume that the shortfall forecast increases marginally. $\frac{da^*_{early}}{d\hat{s}}$ is positive by assumption (a farmer abandons slightly more fields with a higher shortfall). Whether this is good for realized profits depends on the sign of $\frac{d\Pi(s)}{da^*_{early}}$, which ultimately depends on the relative values of $\hat{s}$ and s. If $\hat{s} > s$, or shortfall is already forecasted higher than the realization, then marginally increasing the shortfall makes the information less accurate. $\frac{d\Pi(s)}{da^*_{early}} < 0$; the farmer adapted more than the optimum already. With a higher $\hat{s}$, the farmer would adapt slightly less appropriately than before. However, if $\hat{s} < s$, then marginally increasing the shortfall would make information slightly better, and the adaptive actions would be more appropriate. $\frac{d\Pi(s)}{da^*_{early}} > 0$ because the farmer would have preferred to take more adaptive actions had she known the realized value of the shortfall.

Thus, since I am using realized profit to measure the value of adaptation, the realized value of adaptation can, and often is, negative. Estimating the equation by pooling farmers i together will recover the average realized value of adaptation, which itself might be an interesting value. For example, a negative realized value of adaptation will tell us that over-adapting is more costly than underadapting on average. However, typically we are more interested in how the net profit gained from tailoring investments marginally better. A farmer could tailor her investments better if an erroneously low forecast was marginally higher, and an erroneously high forecast was marginally lower. Separately identifying the β coefficients for these two cases gives a more intuitive estimate of the benefit of adaptation.

5.2 Empirical Methods

I now apply my conceptual framework to data, expanding equation (8) to the panel structure of my dataset.

Equation (9) approximates the thought experiment in the conceptual framework. The most comparable units over time is a county to itself. The panel fixed effects allow me to study how a county's outcomes change marginally adjusting the different shortfall components in different years, relative to the adjustments of all other counties to themselves. I incorporate the intuition from the end of the conceptual framework, by measuring two different coefficients on the shortfall forecast and mid-season shortfall update, for whether the forecasted shortfall is lower than the realization denoted by the indicator $L_{ct} = 1$ or whether the forecasted shortfall is higher than the realization denoted by the indicator $H_{ct} = 1$. Now, $\beta_1^l ow$ is the amount that profit changes due to shortfall increasing by a marginal amount to become more accurate.

$$\begin{aligned} Y_{ct} =& \beta_1^{low} L_{ct}\hat{s}_{ct} + \beta_1^{high} H_{ct}\hat{s}_{ct} + \beta_2^{low} L_{ct}\varepsilon_{ct}^{\text{mid}} + \beta_2^{high} H_{ct}\varepsilon_{ct}^{\text{mid}} \\ &+ \beta_3^{low} L_{ct}\varepsilon_{ct}^{\text{late}} + \beta_3^{high} H_{ct}\varepsilon_{ct}^{\text{late}} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \end{aligned} \tag{9}$$

I use the best agricultural revenues and profits data available, which is at the county level. Therefore, I aggregate my previous district-level dataset to the county level, which is the best way to handle this multi-level data structure (Foster-Johnson and Kromrey, 2018). 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[24] (Department of Water Resources, 2022).

The variation in equation 9 comes from how the average surface water forecast in a county differs across the state within a year. The map in figure **??** shows that districts with similar forecasts are often clustered together, meaning that a lot of the variation across the state will be retained in the county-level dataset.

Y_{ct} measures the agricultural profits in a county, which I construct by subtracting the total agricultural expenses from yearly cash receipts. I have a measure of crop-specific cash receipts, though since I do not have an analogous measure of crop-specific expenses I cannot construct profits and therefore leave these estimates to the appendix. Since 9% of profit observations are negative, I opt to use OLS rather than PPML. Although there are a fair number of outliers, the distribution of the profit data follows a somewhat normal distribution anyway, especially after applying fixed effects. To account for some especially large observations, I winsorize the profits at both ends, at the 5% level. The appendix shows the results are robust to winsorizing instead to the 2.5% or 7.5% levels, and most results stay the same without winsorizing at all.

X_{ct} again controls for non-project water availability from streamflow, precipitation, and depth to the water table, and long-term adaptation through cumulative wells drilled, so 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.

5.3 Results

I plot the net private benefit of ex-ante and mid-season adaptation and the direct effect of water scarcity in figure 13. The estimates are separated by whether the early surface water shortfall forecast was less than or greater than the realization. The coefficients show how profits change directly, or through adaptation if we increased the shortfall forecast in each period by one percentage point.

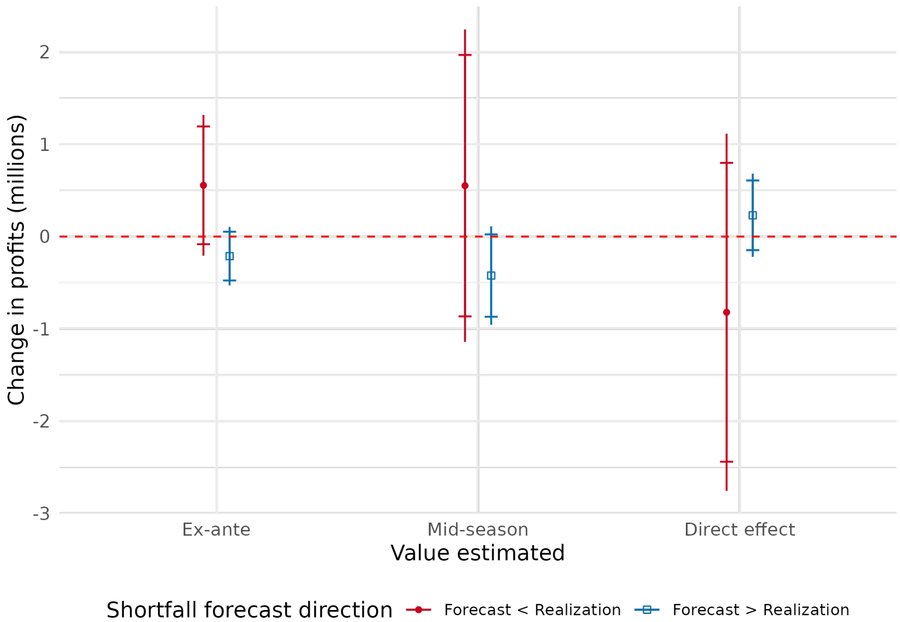
Overall, the results point to adaptation being beneficial in the directions that we would expect. If we increased the shortfall forecast in the years when the shortfall forecast was too low, the average counties would have seen a \$550,000 increase in profits, about 0.4% of average annual profits. These results are not statistically significant, but remain similar magnitudes across winsorization levels. The value of increasing the shortfall forecast by one percentage point when it is too high is statistically significant, and negative. Farmers become worse off when the forecast is less accurate. Recast in terms of accuracy, If the forecast had been one percentage point closer to the actual realization of shortfall, counties would have earned \$212,000 more in the ex-ante period and \$423,000 more in the mid-season period.

The direct effect of surface water shortfall follows a similar pattern. Counties that receive a marginally lower allocation after already having a lower-than-forecasted allocation face a decrease in profits of about \$821,000, about 0.56% of normal. On the other hand, there is suggestive evidence of a slight increase in profits if the surface water shortfall increases to be closer to the forecast.

The standard errors on the erroneously low forecasts are much larger than the standard errors for erroneously high forecasts. Likely, this has more to do with data limitations than a fact about the setting. Only about 10% of observations had erroneously high forecasts, showing that the state successfully meets

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

Figure 13: 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 to recover the value of ex-ante, mid-season and late-season adaptation. Specifically, the first group of coefficients show $\beta_1 - \beta_2$, and the second group shows $\beta_2 - \beta_3$, and the final group shows β_3. The coefficients for the first two groups can be interpreted as the change in profits for a 1 percentage point change in the surface water allocation forecast through adaptation, and the direct effect of the change in shortfall in the last group. The dependent variable, annual agricultural profits, has been winsorized at the 5 and 95% level. The two coefficients for each estimate shows the effect of raising the surface water forecast when it was lower than the realization (in red) and higher than the realization (in blue).

its forecasting goals. Setting a different threshhold for over-forecasts is unclear. In some years, no increase in shortfall might be good and unsurprising (as when the shortfall forecast is already only 5%). In other years, no increase might bad and surprising, as if the year started out with a 50% shortfall forecast and conditions seemed normal. If I could correctly specify beliefs, we would likely see more precision in the case of too-low shortfall forecasts, and likely stronger negative estimates for too-high shortfall forecasts, since they are currently pooled with some estimates that might be positive. Therefore, we should take the plot as suggestive.

The results also show that ex-ante and mid-season adaptation are comparably valuable in my setting. My results cannot conclude anything about the relative value of these forms of adaptation for agriculture generally; rather, the amount that farmers in California benefit from a marginally more accurate shortfall forecast depends on how they have adapted to these forecasts overall. Information available at the early planting season is usually uncertain (correlation between early forecast and final realization: 0.59), while mid-season information is much more accurate (correlation between mid-season shortfall and final realization: 0.91). Therefore, in a case where earlier information was less uncertain, we might see farmers taking more consequential decisions earlier. Or, if earlier information was more certain, farmers might be able to make more beneficial mid-season decisions generally. Thus, the value of adaptation in counterfactual environments is unclear.

Overall, the results show that adaptation to surface water scarcity nearly fully determines farm outcomes in California. Instead of the direct effect surface water shortfall always being bad for farms, the negative effect seems isolated to the case when the realization is already higher than the forecast. Farmers' profits depend on the accuracy of the final shortfall rather than its level. Although the estimating framework cannot recover the value of ex-post adaptation, the direct effect shows at least that farms cannot fully reverse the effects of wrong information in the last period through late-season adaptation. Also, the fact that over-adapting to expected bad conditions is so costly in the short-run might have driven the transition to longer-term adaptation.

6 Discussion: the benefits and costs of agricultural adaptation to surface water scarcity

6.1 The external costs and benefits of adaptation in the short run

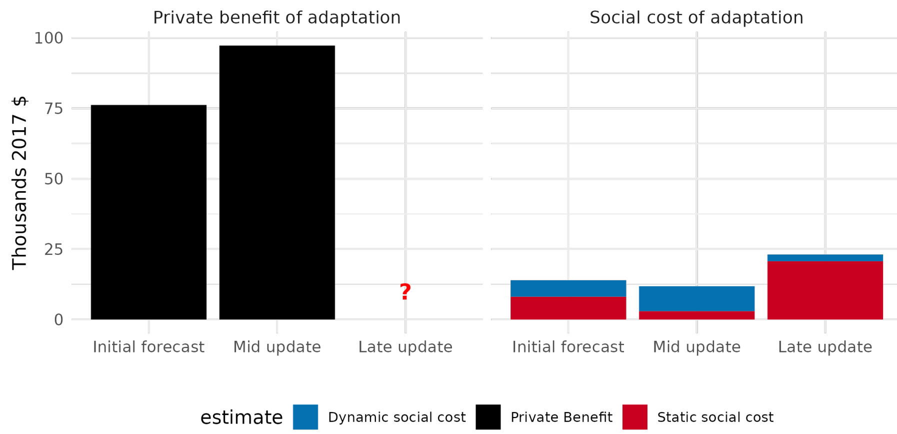
I take my previous estimates to show the average net benefit and external costs of short-run adaptation to a one-unit change in surface water shortfall. Section 3 already estimated the static change in water use from adaptation in a given year. Section 4 showed how much farmers drill wells in response to short-run shocks, which has a small persistence over time. In this subsection, I estimate the change in water use from well drilling specifically tied to short-run shortfall shocks. Then, the final piece required to quantify the costs of adaptation is the social cost of a marginal acre foot of water used.

The longer-run social costs from a one-time shortfall shock occur because of the wells drilled earlier than they otherwise would have been. Section 4 shows how farmers immediately extract large amounts of groundwater, and also transition to even higher intensity crop acreage. I estimate the persistent water use by multiplying the fraction of new wells that persist each year after a shock by the change in groundwater depth over agricultural land, and the aquifer storage constant. I discount the value of water used in later years by a factor of 0.95. The details of the derivation are in the appendix, but the result is shown as the dynamic social cost in figure 14.

It is not obvious how to quantify the value of the excess groundwater extracted. There are no comprehensive empirical estimates for the size of the groundwater extraction externality in California. A few papers describe the externality empirically. (Sears et al., 2017) shows the implied relative groundwater externalities through differences in groundwater pumping. Like my paper, (Bruno et al., 2024) identifies channels through which adaptation leads to externalities in California. Therefore, the best baseline estimate for the externality of groundwater extraction comes from per-unit taxes newly imposed by the Sustainable Groundwater Management Act (SGMA). The act imposes per-acre groundwater pumping fees. The first, lower, tier of fees applies to groundwater units extracted within a basin's 'safe yield,' the amount of extracted groundwater that will be recharged. A second, higher, tier of groundwater fees applies to 'transition water,' groundwater used above safe yield as basins transition to sustainability. The intention of the price is explicitly to curb groundwater use excess of what the state has deemed the socially optimal quantity, and thus can approximate the value of the externality. According to Greenspan et al. (2025), these transition water fees range from \$90 to \$210. I apply the lower bound homogeneously across all regions in my estimates of the social cost of groundwater extraction.

Figure 14 shows the summary of the benefits and costs of a district adapting in the short run to a

Figure 14: Marginal net private value and external costs of short-run adaptation for one district



marginal increase in surface water scarcity. The benefits were estimated for counties in section 5. I divide the estimates by the average number of districts in a county, which is likely an overestimate of the benefit since not all agricultural land is in a water district. These are shown by the black bars in the figure. The static social costs come from multiplying the estimated water use change from figure 7 by the externality, shown by the lower red section of the social cost bars. The dynamic social cost is stacked on top, in blue.

Clearly the benefits outweigh the costs of adaptation for the average district's adaptation choices. However, the social costs are not negligible. In the ex-ante period, the social cost of the average adaptation actions taken make up 18% of the private net benefits, and in the mid-season period, the social cost makes up 12% of the benefits. Although we cannot know for sure the value of ex-post adaptation, if it happened to be as valuable as mid-season adaptation, the social cost would make up almost 25% of the net benefit. The estimates of the value of adaptation depend crucially on the value of the externality. Some groundwater districts have assigned the per-unit groundwater tax more than twice the level that I set, which would result in social costs more than twice as high.

The results reflect the snapshot of benefits and costs for the average district at the average surface water shortfall shock. Intuitively, however, districts continue to adapt with groundwater until the marginal net private benefit of adaptation is zero, or the benefits of adaptation equal the costs. The presence of social costs shifts up the marginal social cost of adaptation. Since the marginal social costs are substantial at the average level of adaptation, as long as groundwater externalities are increasing in extraction, we should expect the social cost to be substantially higher as adaptation increases.

6.2 The benefits and costs of long-run adaptation through well drilling

Social costs make up a substantial portion of adaptation to short-run surface water scarcity. However, my paper shows that over time, farmers in California have transitioned to long-term adaptation through well drilling, which is even more water intensive. In this subsection, I explain what my paper shows about the value of long-run adaptation, and how the definition of adaptation in the literature makes it difficult to define adaptation in my case.

New wells drilled have a net private benefit of around zero. If the net private benefit was much larger than zero, then the farmer would have drilled earlier. However, in section 4 I showed that once a farmer drills a well, she uses around 1800 acre feet of water in the first year, and that quantity likely increases slightly over time. If we add up 1800 acre feet over time, apply a discount rate of 0.95, and an average externality of $35/acre foot, the social cost of drilling a well is $1.26 million dollars. The average well costs between $50,000 and $500,000, meaning that the gross benefit of an average well is much lower than the external costs from drilling. Such high external costs relative to the benefit of wells does not mean that no wells should ever be drilled. Rather, the marginal driller should have a well value of $1.26 million dollars higher than the marginal driller currently does.

Table 3: Value of a new well

Marginal gross private benefit	**Marginal net private benefit**	**External costs**
$0.5 million	$0	$1.26 million

6.3 The joint market failures: climate change and unmanaged natural resources

Farmers overinvest in capital to extract from the groundwater stock because the price of groundwater does not reflect either the scarcity of groundwater, or the physical externalities associated with excess extraction. My paper adds that climate change decreases the quantity of the substitute source of water, which further drove up the private value of groundwater extraction, increasing the social costs of adaptation. Therefore, if unmanaged groundwater is used for adaptation, and if externalities increase in extraction, then climate change increases the social costs of unregulated natural resources. An accurate accounting of the costs of climate change would have to take into consideration the intensification of the market failure from common pool resources. And there are many such cases: agricultural yield reductions could lead to more cleared land in important forests with weak property rights, higher ocean temperatures strains fish populations complicated unmanaged fisheries, and wildfire risk increases the social costs of failing to invest in the public good of forest management. Pricing carbon addresses several market failures at once. However, since carbon is not adequately priced in California, regulators need to impose a second-best groundwater price, which additionally captures how climate change increases the private value of groundwater.

6.4 Information as a potential policy solution in absence of management

In many cases, neither managing the common pool resource, nor pricing carbon is an option politically available to the regulator. California was in this category until 2024, when it began to price groundwater. Prior to 2024, an important policy lever for shifting farmers' behavior was through the presentation of surface water information. Unlike for weather forecasts, the Department of Water Resources and US Bureau of Reclamation issued forecasts for quantities of surface water that the agencies themselves controlled. Thus, the agencies had the best information about their future choices, and issued the most relevant information regarding the surface water available.

As explained in section 1, the agencies used their control over forecasts attempting to meet their objectives of helping farmers' decisions, subject to their own preferences about withholding unreliable forecasts. Further, in 1995 the State Water Resources Control Board asked these agencies to publish conservative surface water allocation forecasts in order to protect environmental flows for endangered species (State Water Resources Control Board, 1995), ostensibly to induce farmers to plan more conservatively even though the average allocation remained the same. The decision was salient and unpopular among water districts, evidenced by the litigation against the US Bureau of Reclamation specifically regarding the conservative statistic (Wes, 1994).

Thus, the forecast characteristics varied over time in a way that most forecasts do not. Therefore, I uniquely have some variation over time in how different information environments led to different adaptation benefits and costs for farmers. Particularly, there were 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 February[25].

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

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

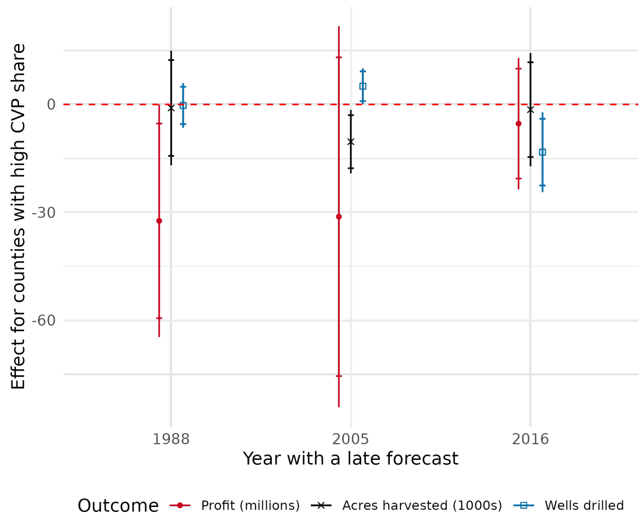
Q_c is an indicator variable for having a high proportion of Central Valley Project water. I use 10% of water coming from CVP as the threshold in the main specification, which is the average amount of CVP water that counties get; about 1/4 of counties get at least 10% CVP water. The results are robust to multiple thresholds, which I include the appendix. D_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 or well drilling 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 $t \in \{1985, 1986\}, t \in \{2004, 2005\}, t \in \{2015, 2016\}$.

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.

Overall, the delay of a Central Valley Project surface water allocation forecast decreased profit for counties with a high amount of 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

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

Figure 15: 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%.

less significant. The magnitudes are economically relevant, however. In 1988, for example, the delay cost the average county more than $30 million, about 10% of the average agricultural profits.

The results for effects on adaptation are less clear. There seemed to be very little effect on acres harvested or well drilling in most years. Well drilling might have increased in response to the delay in 2005, and decreased in response to the delay in 2016 (by 33% of the average county!). These years had very different surface water availabilities, which could explain why the delays might have given different signals. 2005 was a good water year, and 2016 was the last year of a major drought.

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, regardless of the type of water year, and regardless of the adaptation actions they take under uncertainty. The lack of a clear pattern in adaptation shows that adjusting information provision likely will not automatically result in social gains or costs.

7 Conclusion

In this paper, I study how California farmers have adapted to increasing surface water scarcity over time, and the implications of their adaptation on social costs. I built up the story in three parts. First, I studied short-run adaptation strategies, which I grouped into water conserving actions through crop choice, and groundwater intensifying actions through well drilling and groundwater extraction. Farmers took both types of actions in aggregate. However, farmers use more groundwater than they decrease water consumption. Then, I studied the well drilling decision in depth, because it fundamentally changes short-run adaptation options. I found that wells led to a decreasing emphasis on short-term adaptation through annual crop switching, and a transition to a permanent increase in groundwater use and higher water intensity crops, especially perennials. Overall, adaptation to water scarcity led to farmers becoming more dependent on water in an average year. Then, I studied the aggregate net benefit of all actions that farmers took. I found that agricultural adaptation in California is very tailored to the expected level of water availability. The net benefits of short-term adaptation outweigh the social costs, though the social costs make up a substantial fraction. Further, the external costs of a the marginal well outweigh the marginal gross private benefit by a factor of almost 3.

Wells are drilled in part so farmers can adapt to the changing levels of surface water availability in the California. However, since the price of groundwater historically has not included the social costs of extraction, climate change exacerbated the costs of the market failure of the common pool resource. Therefore, this paper quantifies an additional social cost of failure to mitigate climate change. I showed that a simple changing of surface water forecasting rules might improve farmers' outcomes, but does not conclusively change their adaptation in the long run. Policy-makers need to manage groundwater, therefore, not only to address the baseline common pool failure, but also the additional costs imposed when the resource is beneficial for adaptation. Or, policy-makers could address the climate change market failure and improve the costs of many market failures at once.

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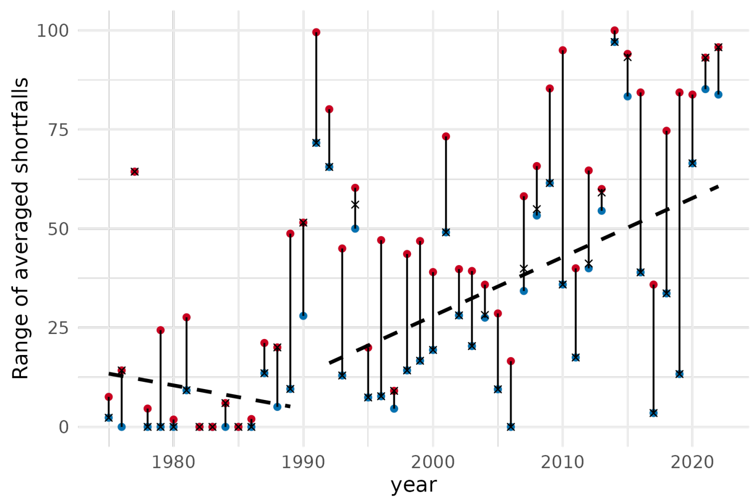
A Data and Context

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

Figure A.1: Range of shortfall within a year and across years



Note: This figure summarizes the surface water allocation shortfall variation within a year and across years. For the within-year variation, I plot the averages surface water shortfalls across contracts for each the February, March and June forecasts. The lowest and highest average shortfall of the year are plotted here, as well as a line to denote the range. An 'x' denotes the final shortfall allocation. I also plot the long-run trends of the final shortfall allocation, with a break at 1992 to illustrate the change in forecasting policy at that point from the Central Valley Project Improvement Act

Table A.1: 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).

required under the Endangered Species Act[26]. 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 Control function approach to control for simultaneous adaptation actions

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

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

Figure A.2: Four examples of how a farmer would encounter a surface water allocation forecast

Advance-Register

Tuesday, December 1, 1992

City eyes new police station

Army paid $124 for 9-inch piece of string

TIP chief may work part time

Season chore

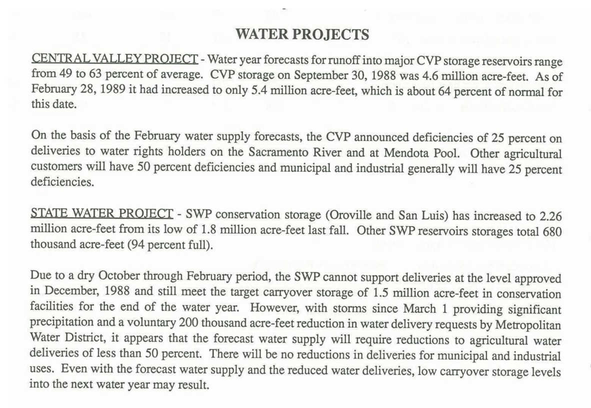
County reps discuss their fiscal plight

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

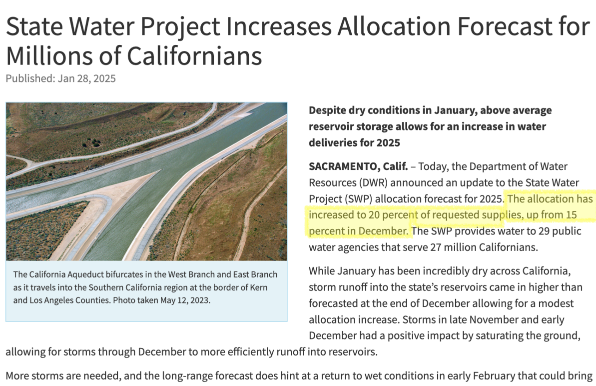
CENTRAL VALLEY PROJECT - Water year forecasts for runoff into major CVP storage reservoirs range from 49 to 63 percent of average. CVP storage on September 30, 1988 was 4.6 million acre-feet. As of February 28, 1989 it had increased to only 5.4 million acre-feet, which is about 64 percent of normal for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

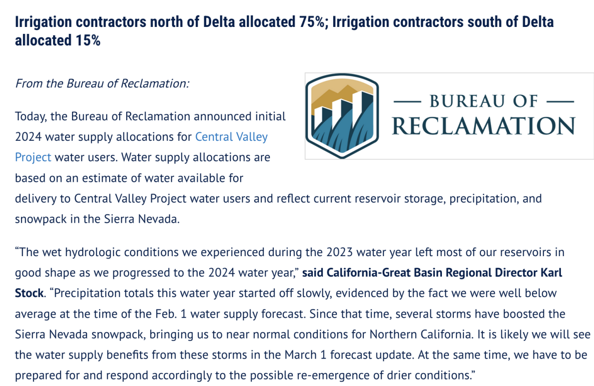
Despite dry conditions in January, above average reservoir storage allows for an increase in water deliveries for 2025

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:

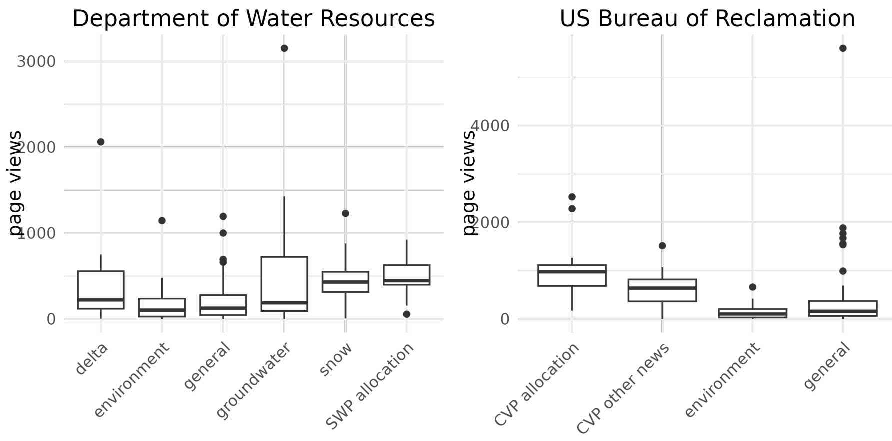
BUREAU OF RECLAMATION

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.3: 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.

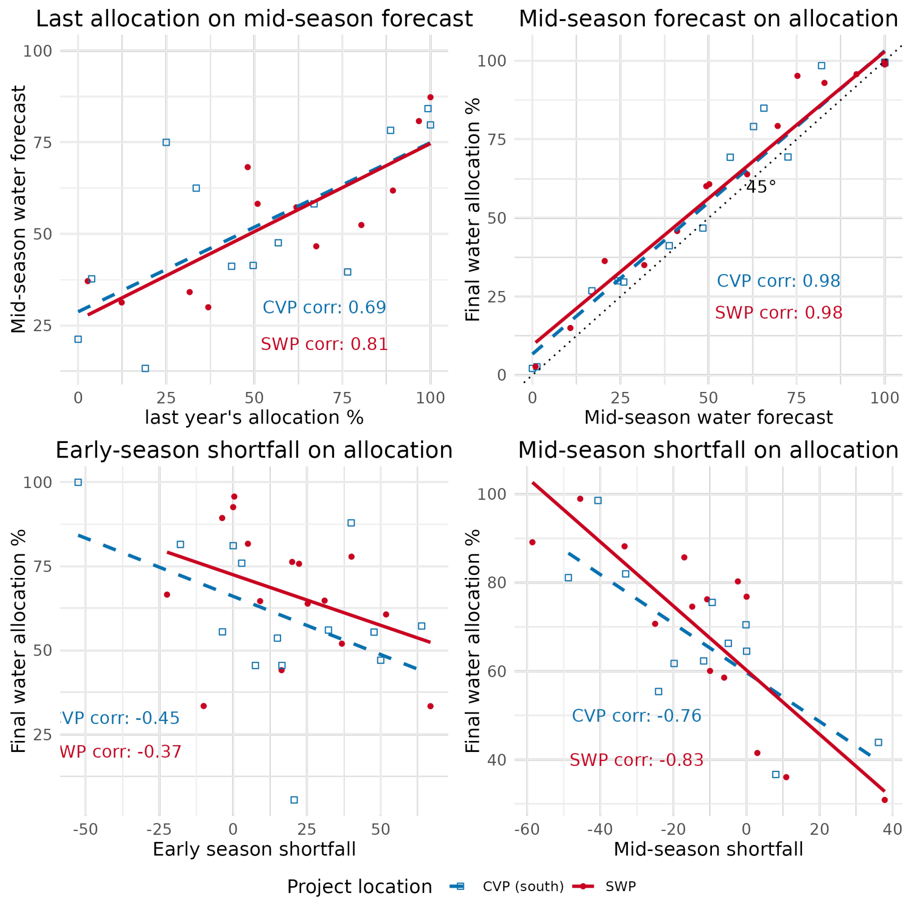
decisions conditional on exogenous variables still includes the effect of the other adaptation choices on the decision. Including those residuals in my regression control for the endogeneity. Although I will not control for all alternate decisions, including control functions for the main adaptation 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. The results using the control function approach are shown in column 3 of each of the regression tables in section B.2.

B.2 Alternative specifications for the main regression, and the coefficient estimates

B.3 Multinomial logit crop responses

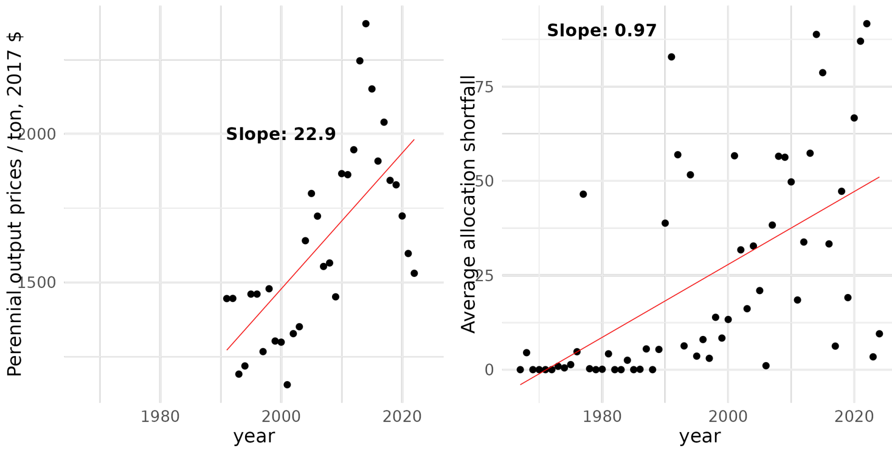
I aggregate the Cropland Data Layer classifications into 7 categories which reflect crops with different planting times, watering intensities, and planting intensities to reflect the qualitatively different substitutions available. Low-water crops are typically planted in the winter, and are usually grains. High-water crops are typically planted late in the year, like rice and cotton. I also include a category for mixed-water crops, which can be low-water if they are planted early, and high-water if they are planted late, like many vegetables. Double crops have two or more planting times, like alfalfa and double-cropped grains. Perennial (permanent) crops include fruit trees and nut trees. The last two categories are idled fields, and non-agricultural fields.

Figure A.4: Relation of project forecasts to each other: across districts and across months in a year



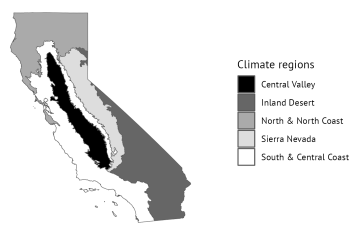
Note: The top left panel shows how the binned average of last year's surface water allocation percent corresponds to the average late-planting season surface water forecast (before April 1st) for the State Water Project (in red dots and solid line) and the Central Valley Project's southern districts, (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 A.5: Caption



Note:

Figure A.6: California ecological regions



Note: This map shows the five major ecological regions in California relevant for agriculture, shows climate regions across the state, aggregated up from level 3 ecoregions to crop planting regions (UC Master Gardener Program, 2025). The regions differ by growing season, and also generally in water availability. The Central Valley has a long growing season, and access to a deep aquifer. The South and Central Coast has cooler weather, with some important aquifers. The Inland desert region has an early planting season (winter) and has minimal groundwater and relies heavily on surface water supplies. There is minimal cropland in the North Coast and Sierra Nevada, and I observe no water districts in these two regions

Figure A.7: Farm outcomes on final shortfall, only controlling for time trends and mean shortfall

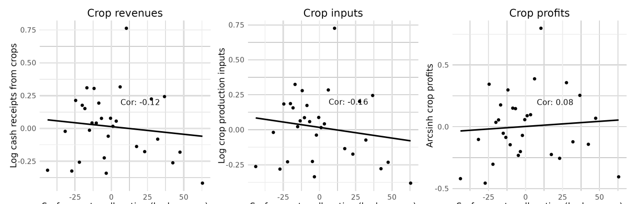


Table A.2: Typical crops at each planting time by region, and watering requirement

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

$$\begin{aligned}\mathbb{C} =\{&\text{low-water}, \text{high-water}, \text{mixed-water}, \\ &\text{double-cropped}, \text{non-ag}, \text{idle}, \text{perennial}\}\end{aligned}$$

Consider a farmer i who decides every year whether to plant her field in one of each seven crop categories. Of course, some of these decisions are dynamic, and several papers have modelled the dynamics of the decision ((Scott, 2014), Burlig et al. (2020)). My simpler model is intended to capture short-term annual cropping decisions relative to the dynamic category (perennials) which I find in my main empirical specification does not respond very much to short-term information.

The simple multinomial logit model is shown in equation B.3. The fraction of all of the fields planted in crop $c, j \in \mathbb{C}$ depends on the shortfall information, as well as other controls including the district-level past wells drilled, field crop prices, weather, depth to the water table, ecological region, groundwater availability, and total average water availability.

$$P(c_{it}|Z_{it}, \mathbb{C}, \beta) = \frac{e^{Z^c_{it}\beta}}{\sum_{j\in\mathbb{C}} e^{Z^j_{ft}\beta}}$$

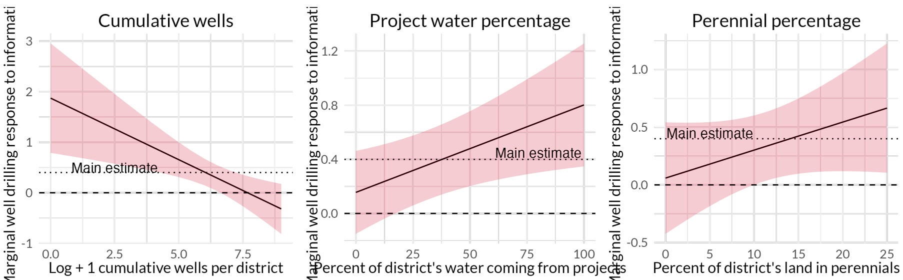
The results are shown in table B.8.

B.4 Heterogeneity results

B.5 Other results

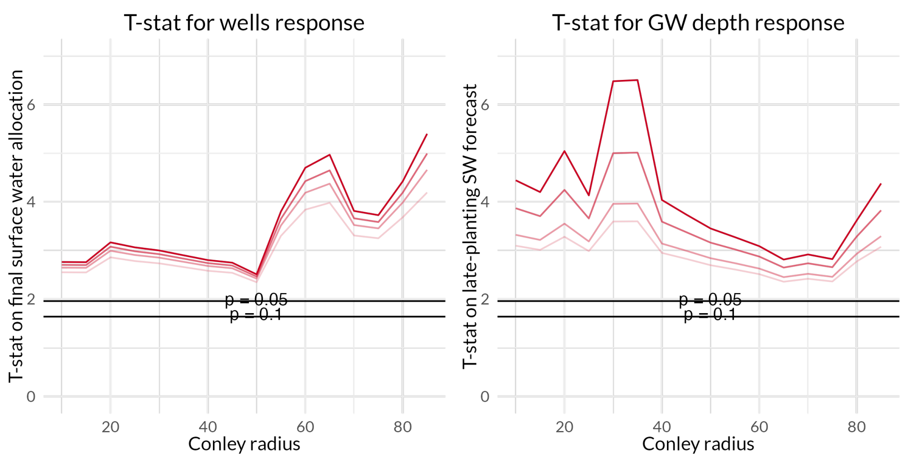
B.6 Distributions

Figure B.1: 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.2: 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.11, 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.

Figure B.3: Distributions of residuals using OLS

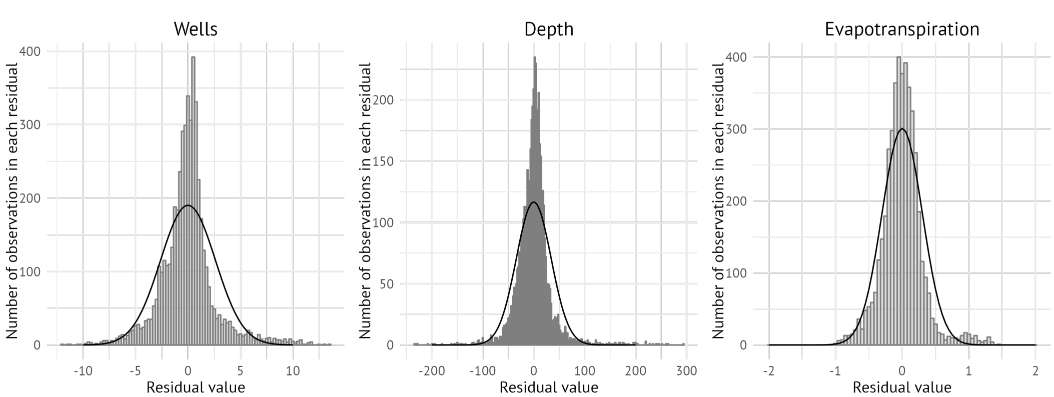


Table B.1: Well drilling responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.28	0.25	0.30	0.28***	0.15	0.33
	(0.18)	(0.18)	(0.18)	(0.10)	(0.11)	(0.37)
Mid-season shortfall update	0.25*	0.23	0.25*	0.25***	0.28*	0.13
	(0.15)	(0.14)	(0.14)	(0.06)	(0.16)	(0.23)
Late-season shortfall update	−0.01	−0.02	−0.01	−0.01	0.01	−0.83*
	(0.14)	(0.14)	(0.14)	(0.12)	(0.15)	(0.42)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4674	4686	4640	4674	4697	4910
Pseudo R^2	0.61	0.61	0.61	0.61	0.61	0.75

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

Note: These columns show six alternate specifications for the well drilling response to surface water shortfalls from section 3. The dependent variable is the total number of wells drilled in a district between January and August. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.2: Depth to groundwater responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.04	-0.01	0.03	0.04	0.06	-2.02
	(0.07)	(0.08)	(0.08)	(0.05)	(0.08)	(9.63)
Mid-season shortfall update	0.02	-0.00	0.01	0.02	0.02	-2.09
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(6.34)
Late-season shortfall update	0.08^{*}	0.04	0.09^{**}	0.08^{***}	0.07^{*}	2.31
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(4.54)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4923	4923	4488	4923	4950	4923
Pseudo R^2	0.75	0.75	0.76	0.75	0.75	0.81

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

Note: These columns show six alternate specifications for the change in depth to the groundwater table response to surface water shortfalls from section 3. The dependent variable is the level depth to the groundwater table in the dry season (absolute value) in feet. The change in depth to the groundwater table is a proxy for groundwater extraction. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the regional groundwater depth as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.3: Evapotranspiration responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	−0.01	−0.00	−0.04	−0.01	−0.03	−0.09
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.09)
Mid-season shortfall update	−0.01	−0.00	−0.02	−0.01	−0.00	−0.05
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.06)
Late-season shortfall update	0.03	0.03	0.02	0.03	0.03^{*}	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4500	4513	4465	4500	4524	4500
Pseudo R^2	0.18	0.18	0.18	0.18	0.18	0.85

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

Note: These columns show six alternate specifications for the evapotranspiration response to surface water shortfalls from section 3. The dependent variable is average evapotranspiration, measured in meters per year. Evapotranspiration is a proxy for the total amount of water applied. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.4: Idling responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.18	0.24^{*}	0.15	0.18	0.13	-307.90
	(0.12)	(0.12)	(0.13)	(0.11)	(0.14)	(412.74)
Mid-season shortfall update	0.24^{***}	0.25^{***}	0.19^{**}	0.24^{***}	0.26^{***}	227.67
	(0.08)	(0.08)	(0.09)	(0.06)	(0.07)	(282.99)
Late-season shortfall update	0.40^{***}	0.44^{***}	0.38^{***}	0.40^{***}	0.44^{***}	504.41^{*}
	(0.07)	(0.07)	(0.08)	(0.10)	(0.07)	(281.03)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1938	1946	1934	1938	1940	1938
Pseudo R^2	0.98	0.98	0.98	0.98	0.98	0.94

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

Note: These columns show six alternate specifications for the idling response to surface water shortfalls from section 3. The dependent variable is the number of idled acres in a district. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.5: Perennial planting responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.05	0.12	0.05	0.05	0.09	-343.18
	(0.10)	(0.12)	(0.10)	(0.09)	(0.09)	(473.86)
Mid-season shortfall update	0.02	0.03	0.02	0.02	-0.00	-341.25
	(0.05)	(0.06)	(0.05)	(0.04)	(0.06)	(227.19)
Late-season shortfall update	0.03	0.06	0.03	0.03	-0.01	-1041.44^{**}
	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)	(397.17)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1938	1946	1934	1938	1940	1938
Pseudo R^2	0.98	0.98	0.98	0.98	0.98	0.97

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

Note: These columns show six alternate specifications for the perennial response to surface water shortfalls from section 3. The dependent variable is the number of perennial acres in a district. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. Perennial acreage is primarily a placebo, since farmers should not drastically adjust permanent acreage in response to surface water shocks. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.6: High-water cropping responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	-0.24^{**}	-0.22^{**}	-0.26^{**}	-0.24^{*}	-0.35^{***}	669.52
	(0.11)	(0.09)	(0.10)	(0.12)	(0.08)	(525.62)
Mid-season shortfall update	-0.19^{**}	-0.20^{**}	-0.20^{**}	-0.17	-0.14	202.51
	(0.09)	(0.09)	(0.09)	(0.11)	(0.10)	(209.02)
Late-season shortfall update	-0.25^{**}	-0.24^{**}	-0.26^{**}	-0.25^{*}	-0.17	386.37
	(0.11)	(0.11)	(0.11)	(0.13)	(0.14)	(371.64)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1906	1914	1902	1906	1908	5774
Pseudo R^2	0.99	0.99	0.99	0.99	0.99	0.38

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

Note: These columns show six alternate specifications for the high-water acreage response to surface water shortfalls from section 3. The dependent variable is the number of high-water annual acres in a district, which are typically planted late in the planting season. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.7: Low-water cropping responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.35^{***}	0.38^{***}	0.35^{***}	0.35^{**}	0.45^{***}	750.47^{**}
	(0.10)	(0.09)	(0.10)	(0.16)	(0.11)	(363.10)
Mid-season shortfall update	0.26^{***}	0.29^{***}	0.25^{***}	0.26^{*}	0.24^{***}	355.39^{**}
	(0.10)	(0.10)	(0.09)	(0.15)	(0.09)	(163.32)
Late-season shortfall update	0.17^{**}	0.17^{**}	0.22^{***}	0.17	0.11	424.00
	(0.08)	(0.08)	(0.08)	(0.18)	(0.08)	(257.65)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1906	1914	1902	1906	1908	5774
Pseudo R^2	0.97	0.96	0.97	0.97	0.97	0.37

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

Note: These columns show six alternate specifications for the low-water acreage response to surface water shortfalls from section 3. The dependent variable is the number of low-water annual acres in a district, which are typically planted earlier in the planting season. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.8: Multinomial logit: response of crop choice to forecast shortfall

varname	double	early	idle	late	mixed	non_ag
(Intercept)	20.181***	10.027***	9.471***	12.864***	13.805***	5.75***
	(0.087)	(0.136)	(0.32)	(0.287)	(0.31)	(0.314)
Baseline forecast	1.063***	0.771***	0.367***	-0.052	0.084**	0.01
	(0.062)	(0.068)	(0.051)	(0.05)	(0.038)	(0.04)
Mid shortfall update	0.43***	0.259***	0.094*	-0.044	0.165***	0.098***
	(0.063)	(0.07)	(0.052)	(0.05)	(0.039)	(0.041)
Late shortfall update	0.544***	-0.086	-0.064	-0.33***	0.156***	0.252***
	(0.073)	(0.078)	(0.059)	(0.057)	(0.045)	(0.051)
Log lag cumulative wells	-0.278***	-0.485***	-0.647***	-0.568***	-0.232***	-0.249***
	(0.015)	(0.016)	(0.013)	(0.013)	(0.011)	(0.012)
Rainfall	-0.001***	-0.001***	0.001**	-0.001**	0.002***	0.002***
	(0)	(0)	(0)	(0)	(0)	(0)
Temperature	-0.132***	-0.125***	0.08***	-0.128***	0.036***	0.035***
	(0.013)	(0.015)	(0.01)	(0.011)	(0.008)	(0.008)
Central Valley = 1	4.488***	3.255***	1.341***	4.423***	0.899***	-2.442***
	(0.178)	(0.236)	(0.118)	(0.214)	(0.116)	(0.115)
Inland Desert = 1	4.612***	1.902***	4.472***	2.078***	3.357***	1.939***
	(0.342)	(0.332)	(0.162)	(0.139)	(0.162)	(0.155)
Sierra Nevada = 1	7.544***	1.825***	2.41***	3.067***	6.635***	6.277***
	(0.305)	(0.003)	(0.014)	(0.008)	(0.204)	(0.183)
South Coast = 1	3.537***	3.045***	1.248***	3.296***	2.914***	-0.024
	(0.193)	(0.242)	(0.123)	(0.22)	(0.12)	(0.118)
GW depth in 2000	-0.583***	-0.513***	-0.497***	-0.638***	0.029**	0.244***
	(0.015)	(0.017)	(0.014)	(0.013)	(0.014)	(0.016)
log(-1 * lag_depth)	0.116***	0.122***	0.18***	0.234***	-0.246***	-0.164***
	(0.021)	(0.023)	(0.018)	(0.018)	(0.016)	(0.019)
Log area (km^2)	0.22***	0.48***	0.523***	0.534***	0.159***	0.432***
	(0.016)	(0.018)	(0.013)	(0.013)	(0.012)	(0.013)
Log groundwater use	-0.008*	0.001	-0.02***	0.003	-0.01***	-0.13***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
log(price_field)	-3.694***	-2.037***	-1.778***	-2.464***	-2.313***	-0.754***
	(0.044)	(0.064)	(0.07)	(0.084)	(0.065)	(0.065)
Log non-project ag water	0.004	0.017***	0.025***	0.01***	0.035***	-0.062***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)

Note: These are the log-odds coefficients of a multinomial logit model of crop choice in response to information throughout the growing season. The omitted category is perennial acreage, which I show in my main results respond very little to short term information because of the high cost of switching crops from year to year. 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.9: Heterogeneity by location

	Extraction	Total water	Idling
Baseline shortfall	-0.06	-0.19^{***}	-0.13
	(0.08)	(0.05)	(0.26)
Mid-season shortfall update	-0.02	-0.33^{***}	0.11
	(0.08)	(0.07)	(0.15)
Late-season shortfall update	-0.07	0.02	0.07
	(0.10)	(0.04)	(0.15)
Baseline × Central Valley	0.15	0.21^{***}	0.26
	(0.10)	(0.03)	(0.24)
Baseline × Desert	-0.36^{***}	0.05	0.13
	(0.12)	(0.06)	(0.25)
Mid update × Central Valley	0.07	0.37^{***}	0.18
	(0.09)	(0.06)	(0.16)
Mid update × Desert	-0.22^{*}	-0.48^{***}	0.31^{*}
	(0.13)	(0.15)	(0.17)
Late update × Central Valley	0.19^{*}	0.02	0.33^{**}
	(0.10)	(0.04)	(0.14)
Late update × Desert	-0.03	0.27^{**}	0.50^{***}
	(0.19)	(0.12)	(0.17)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall components by an indicator for whether the district is in the South and Central Coast (baseline category), the Central Valley or the Inland Desert, shown in the map in Appendix figure A.6. The baseline category in the first three rows are the districts in the temperate coastal region. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

Table B.10: Heterogeneity by news

	Extraction	Total Water	Idling
Baseline shortfall	-0.00	-0.03	0.08
	(0.08)	(0.04)	(0.16)
Mid-season shortfall update	-0.04	-0.00	0.12
	(0.06)	(0.03)	(0.14)
Late-season shortfall update	0.02	-0.02	0.39^{*}
	(0.03)	(0.03)	(0.23)
Mid update × Bad news	0.05	-0.02	0.11
	(0.06)	(0.04)	(0.17)
Late update × Bad news	0.07	0.09^{***}	0.56^{**}
	(0.05)	(0.02)	(0.26)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall updates by an indicator for whether the district received bad shortfall news, defined by the shortfall increasing, or by the shortfall equalling zero given a low initial surface water shortfall forecast. The baseline category is good surface water news. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

	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.11: 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.12: 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.11, 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.13: 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.11 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.