Farmer Response to Policy Induced Water Reductions: Evidence from the Colorado River*

Link to publication

Lena Harris

[a] *University of Rochester*

Abstract

Surface water supplies are becoming increasingly strained, pushing policy makers to find solutions to facilitate reductions in water use though there is limited evidence on how farmers respond to policy induced variation in surface water supplies. This paper uses a difference-in-differences framework to compare the response of farmers to a bundle of policies reducing deliveries from the Colorado River by 35%. I find that on average, farmers reduce the amount of land planted but plant more water intensive crops leading to a minimal reduction in total estimated water use compared to the counterfactual. Additionally, there is strong suggestive evidence that farmers are using groundwater to offset a significant amount of the surface water loss. These findings have important consequences for understanding the relative trade-offs policy makers face when implementing policies that protect surface water sources.

Keywords: agricultural production, drought, groundwater, water policy.
JEL: Q15, Q25, Q28, Q38, Q54

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Email address: h.harris@rochester.edu (Lena Harris)

1. Introduction

Surface water supplies are becoming increasingly strained as growing population increases demand while climate change reduces supply. Policy makers are facing increased urgency in dealing with surface water scarcity, because surface water supplies water to residents in some of the largest cities and over 20 million acres of agriculture in the US alone (USDA National Agricultural Statistics Service, 2018). Concern over growing scarcity has led to an increase in policy interventions aimed at reducing surface water use, though there is little empirical evidence about the direct consequences of the possible policy choices.

This paper examines the agricultural consequences of a bundle of policies implemented to reduce the use of surface water from the Colorado River. The Colorado River is a relevant context, as it is both highly over-allocated and an important water source for much of the American Southwest. About 85% of its water irrigates 5.5 million acres of farmland while the remaining water supplies over 10 million people in major cities such as Los Angeles, San Diego, Las Vegas, and Tijuana (Maupin et al., 2018). The analysis relies on a natural experiment, where a subset of Arizona farmers experienced a bundle of policy shocks which reduced the volume of water deliveries from the Colorado River to these farmers by 35% from 2015-2021. The reduction in deliveries was achieved through two sequential policies: 1. a reduction in surface water prices in exchange for a reduction in water deliveries from 2015-2019 (here on denoted as the Forbearance Program), which was then completely replaced by 2. a quantity restriction on surface water supplies in 2020-2021 (here on denoted the Federal Restriction). Under both policies, preexisting minimum delivery requirements were removed.

Variants of these two policies are common for regulating natural resources. For example, "feebates" like the Forbearance Program have been used to reduce agricultural fertilizer use, vehicle emissions, and municipal water use (Scholz and Geissler, 2018; Samano, 2017; Collinge, 1996). These programs differ from other financial incentives like taxes and usage fees by charging a fee but offering a rebate for low use. Similarly, input restrictions like the Federal Restriction are commonly used in emissions regulation, livestock antibiotic use, and especially fishery management (Caron et al., 2015; Belay and Jensen, 2021; Dupont, 1991; Pascoe and Robinson, 2008). With both policy approaches there are concerns about unintended consequences such as welfare loss for producers, spatial leakage, and substitution to other resources. This paper uses the Forbearance Program and Federal Restriction to evaluate the potential consequences of these two types of policies in the context of water used for agricultural production.

The analysis in this paper relies on a difference-in-differences framework, comparing the subset of Arizona farms exposed to the policy bundle to similar farms elsewhere in Arizona and southern California. To construct the control group, I first link parcels in the study region to remote sensed crop data and environmental characteristics. I then identify the set of parcels that are in irrigation districts served by the Colorado River, and from these use propensity score matching to select a set of control parcels that are similar to the parcels exposed to the policies. With these two groups, I use difference-in-differences to estimate changes in cropping decisions such as the amount of crops planted and the types of crops planted due to the policy bundle.

I find that in contrast with the large reduction in surface water deliveries achieved by the policies, on average there was a limited impact on the total water intensity of plantings. The estimated average water intensity of plantings per acre was minimally affected by the reduction in surface water since water savings from reductions in the amount of land planted (8 percentage points) were offset by increases in the amount of alfalfa (a relatively water intensive crop) planted. Additionally, I find evidence of increases in cumulative evapotranspiration, as a coarse measure of water applied, suggesting deficit irrigation was not extensively adopted. Further analyses provide evidence that the average response was heterogeneous with respect to estimated groundwater costs, where those with more expensive groundwater were more adversely affected by the policy. This suggests that the main result is driven in part by input substitution, with groundwater replacing the reduced Colorado River water.

This paper contributes to the existing literature on resource management by quantifying the effects of the Forbearance Program and Federal Restriction. An important take away is that while the policies are successful at reducing river water use, farmers reduce planting and potentially substitute towards groundwater. This aligns with previous work which has shown that groundwater plays a valuable role in smoothing surface water shocks (Tsur and Tomasi, 1991; Mukherjee and Schwabe, 2015; Smith and Edwards, 2021). Additionally, while groundwater substitution has already been acknowledged by CAP stakeholders, the quantification of the effects by this paper are important for the discussion on how to regulate water moving forward when there are input substitution effects.

This paper also contributes more narrowly to existing work on water scarcity by presenting new evidence on how farmers respond to policy induced reductions in surface water access. Much of the previous work on adaptation to surface water scarcity has relied on identification from short term, inter-annual variation in precipitation (Manning et al., 2017; Ji and Cobourn, 2018; Xie et al., 2019; Cobourn et al., 2021; Hagerty, 2021), instead of anticipated policy implementation. Because the policy shock exposes farmers to less uncertainty, they may be able to more fully offset the expected surface water loss and resulting output loss. At first blush this appears true, as I find the total water intensity of plantings was not substantially impacted. However, this average change appears to be the result of an increase in the water intensity of planted land and a decrease in the amount of planted land. Interestingly, I find a similar, though slightly smaller, response for the amount of land planted under the policy-induced variation (a 21% increase in fallowed land due to a 35% reduction in surface water deliveries) as Hagerty (2021) finds for precipitation induced variation for farmers in California (a 26% increase in fallowing for a 33% reduction in surface water supply). Other research on surface water scarcity has focused on adaptation to long-run, gradual changes in water access (Burke and Emerick, 2016; Hornbeck and Keskin, 2014; Fishman et al., 2019; Smith, 2021; Feng et al., 2012; Gray and Wise, 2016; Nawrotzki et al., 2017; Blakeslee et al., 2020) as opposed to sudden shocks, while I am able to identify farmer adaptation to a sudden change in water access.

Lastly, this paper is able to compare the relative merits of two different policy approaches aimed at reducing surface water demand in a fixed context. To my knowledge there is no empirical evidence directly comparing how farmers respond to different policies regulating surface water access. Existing research has instead focused on understanding farmer response to singular policies regulating water access, either through pricing (Fishman et al., 2016; Smith et al., 2017; Hrozencik et al., 2021; Burlig et al., 2021) or quota restrictions (Drysdale and Hendricks, 2018), making direct comparison difficult since the contexts of each are different. While consideration needs to be given to the sequential nature of the policies examined in this analysis, it is still relevant and informative to compare the different outcomes since the set of exposed farmers, concurrent policies, and resulting water reductions are identical across the two.

Details of the policies and historical context used for identification are presented in section 2. I then provide a conceptual framework for considering adaptation strategies in section 3. Data and the empirical methodology are outlined in section 4. The main results are presented in section 5 and discussed in section 6. Section 7 concludes.

2. Background

2.1. Central Arizona Project

The construction of the Central Arizona Project (CAP), a 336 mile long canal from the Colorado River to central Arizona, was approved in 1968 and completed in 1993. The goal for the canal was to bring about 1.6 million acre-feet[1] (AF) of water to central Arizona to supply growing urban areas and reduce groundwater extraction by agricultural users (Central Arizona Project, 2016a). To enforce reductions in groundwater use, two stipulations were attached to CAP water access with regards to groundwater. The first was that CAP recipients were not allowed to pump groundwater from within the service area for use outside of the service area (Central Arizona Project, 2016a). The second was that users must use their entire allotment of "reasonably available" CAP water before being able to use groundwater (Central Arizona Project, 2002). In combination, these two policies limited the availability of groundwater access for farmers in the CAP service area.

The Central Arizona Water Conservation District (CAWCD), which manages CAP water supplies, defines its service area as three counties: Pima, Pinal, and Maricopa. Within these three counties, CAP delivers water to Native Nations, municipal systems, industrial users, and irrigation districts (Ikeya, 2021). Irrigation districts are regional organizations that coordinate water deliveries from CAP to end use farmers and manage infrastructure (e.g. canals, pumps, and wells), benefiting from economies of scale. CAWCD allocates water to irrigation districts based on the number of CAP eligible acres in the irrigation district, with CAP eligibility defined by being irrigated between 1958 and 1968 (Central Arizona Project, 2016a). While there are 15 irrigation districts CAWCD identifies as consistently serving, the number of districts served is subject to water availability and demand, with more or

[1] An acre-foot of water is the volume of water required to cover an acre of land in water to a depth of one foot.

fewer irrigation districts receiving water in any given year. Since 2010, 12 districts have received deliveries from CAP.

Originally, irrigation districts were entitled to a fixed share of CAP water, but the price of this water was unaffordable (Central Arizona Project, 2016a). The Arizona Water Settlement Act of 2004 renegotiated water diversions to provide cheaper, but not guaranteed, water to irrigation districts. Since 2004 irrigation districts are entitled to "Ag Pool" water, which is the leftover part of Arizona's allotment of Colorado River water after all other entitlements (Native Nations, municipal, and industrial) have been filled. Irrigation districts are charged delivery rates per AF by CAWCD to offset the energy costs for delivery (Central Arizona Project, 2016a). The Ag Pool water supply from 2004 to 2014 was consistently around 400,000 AF (Central Arizona Project, 2023).

The delivery process of water within irrigation districts to farmers is heterogeneous. In the largest district, the Maricopa-Stanfield Irrigation and Drainage District, farmers order water deliveries from the district, constrained by an annual allotment which is determined by previous use and acreage, and pay per AF an almost equivalent rate as what the district is charged (Maricopa-Stanfield Irrigation and Drainage District, 2021a,b). In San Carlos Irrigation and Drainage District, farmers receive water from both CAP and the San Carlos Reservoir, with CAP water being available only to farms with at least 5 acres of land. Additionally, farmers are required to purchase their full allotment of Colorado River water and are charged at a mark up per acre of land (San Carlos Irrigation and Drainage District, 2022). Under drought conditions, the Maricopa-Stanfield Irrigation and Drainage District reports drilling new groundwater wells and rehabilitating old wells, while the San Carlos Irrigation and Drainage District reports relying on water in the San Carlos Reservoir (Maricopa-Stanfield Irrigation and Drainage District, 2021b; San Carlos Irrigation and Drainage District, 2022).

2.2. Forbearance Program

In 2014, CAWCD announced the start of the Ag Pool Forbearance Program, beginning in 2015. The goal of the program was to reduce use of Ag Pool water and leave the forgone supplies in Lake Mead to help buffer declining lake levels due to drought (Central Arizona Project, 2017). Under the Forbearance Program, districts who had used their entire CAP allotment in four of the five preceding years could agree to reduce their water deliveries. In exchange, these districts would receive reduced costs on the water that they did receive, and had the stipulation that they must use all of their allotted CAP water before any groundwater waived (Ikeya, 2021).

The Forbearance Program consisted of five separate phases, each of which offered a variation of reductions in CAP deliveries in exchange for discounts on remaining deliveries (Appendix Table A3 details the differences in the phases). Under the first phase, Ag Forbearance 1, irrigation districts agreed to forbear at least 23% of their CAP allotment and at most the lesser of 75% or 20,000 AF of their allotment. In exchange for reducing deliveries, the districts would receive reduced pumping charges on their remaining deliveries of \$36/AF and \$38/AF in 2015 and 2016 respectively (Central Arizona Project, 2014). The Ag Forbearance 2 Program allowed participants in Ag Forbearance 1 to further reduce deliveries by 12% in 2016 in exchange for a discount of \$8/AF on deliveries in 2017 and 2018 (Central Arizona Project, 2015). Forbearance Programs 4 and 5, implemented over 2018-2019, followed a similar structure of discount in exchange for fallowing.

In contrast to programs 1,2,4 and 5, Ag Forbearance 3 offered no compensation to participating districts but allowed districts to reduce their CAP water deliveries (Central Arizona Project, 2016b). The program was initially implemented in 2016, but was then extended indefinitely. In essence, Ag Forbearance 3 waived the requirement that CAP recipients use their full allotment of "reasonably available" Ag Pool water before being able to use groundwater, though districts were still subject to other groundwater regulation. This resulted in 6 of the 12 irrigation districts receiving no CAP water at some point between 2016 and 2019.

While each phase of the larger Forbearance Program was heterogeneous in implementation, the policy approach was consistent between 2015 and 2019. Irrigation districts were allowed to voluntarily reduce water deliveries from CAP. In exchange they received discounted delivery rates on the water they did receive. Additionally starting in 2016, irrigation districts were not required to use their full CAP allotment before using alternative, potentially cheaper water sources. The reduction in deliveries to CAP Ag Pool users over time starting in 2015 is highlighted in Figure 1, which shows volumes of annual Ag Pool water delivered via CAP (Central Arizona Project, 2023). Figure A1 of the appendix breaks down deliveries to the 12 recipient irrigation districts, and shows every district experienced a reduction in deliveries to some extent between 2015 and 2019.

Figure 1: CAP Water Deliveries

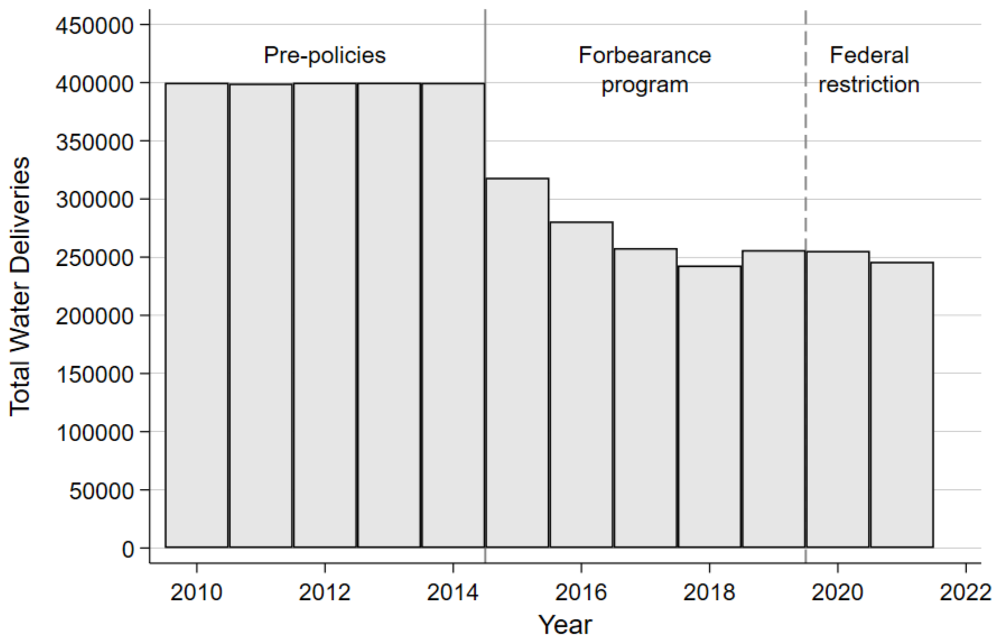


Figure plots the total amount of Ag Pool deliveries from the Colorado River to irrigation districts via the Central Arizona Project (CAP). Deliveries are measured in acre feet of water. The vertical lines denote the beginning of the Forbearance Program in 2015 and Federal Restriction in 2020. Data on water deliveries over time is publicly available on the CAP website.

2.3. Federal Restriction

The Lower Basin Drought Contingency Plan was agreed upon by stakeholders in Arizona, Nevada, and California in May of 2019. The Drought Contingency Plan (DCP) defined threshold levels, based on the water levels in Lake Mead, at which water deliveries from the Colorado River would be curtailed (Bureau of Reclamation, 2019). The thresholds and their respective curtailments are shown in Figure A2. The Tier 0 Federal Restriction was set to be enacted for a given year if predicted levels for Lake Mead on January 1st of that year were below 1,090 ft but above 1,075 ft. Under a Tier 0 restriction, Arizona agreed to reduce Colorado River water deliveries by 192,000 AF. This reduction in delivery is not directly compensated and enforced by the Department of the Interior who manages the deliveries from the Colorado River to Arizona, Nevada, and California (Bureau of Reclamation, 2019).

In August of 2019, the U.S. Bureau of Reclamation released their predicted levels for Lake Mead, showing predicted levels to be below 1,090 ft (U.S. Bureau of Reclamation, 2019). Because of the DCP agreement, this resulted in the implementation of a Tier 0 restriction starting in 2020, reducing Arizona's deliveries[2] . Because the Ag Pool water from CAP is the "excess" part of Arizona's Colorado River supply, the reduction in deliveries came entirely from the CAP Ag Pool meaning that only farmers using CAP Ag Pool water were affected by the restriction (Central Arizona Project, 2021). Other Colorado River water users in Arizona and California were unaffected. Due to continued declines in Lake Mead levels, the Tier 0 restriction continued into 2021 and was upgraded to a Tier 1 restriction in 2022.

Additionally, while the forbearance program incentivized voluntary reductions in water deliveries, the Tier 0 restriction made reductions no longer voluntary. This implicitly means that the Tier 0 restriction completely replaced the Forbearance Program starting in 2020, though the restrictions on alternative water sources remained lifted (Ag Program 3). Direct comparison of the Forbearance Program and Federal Restriction is shown in Table 1.

[2]The Arizona DCP Implementation Plan consists of agreements on how Arizona will implement different parts of the DCP should they occur, including a section outlining state managed water transfers to CAP. The Arizona DCP Implementation Plan only accounts for Tier 1 restrictions and above and does not require mitigating water supplies be sent to CAP under a Tier 0 restriction.

Table 1: Comparison of Forbearance Program and Federal Restriction

	Pre-policy	Forbearance Program	Federal Restriction
Year announced		2014	2019
Years implemented		2015-2019	2020-2021
Maximum total deliveries	400,000af	400,000af	257,000af
Minimum delivery	Must use full allocation	No	No
Surface water price range	[$39, $49]	Discounted: [$36, $55]	[$56, $56]
		Undiscounted: [$53, $63]	

Table compares water deliveries, prices, and groundwater regulations for CAP users under the two policies. Prices are from historic water delivery reports (2010-2014) (https://www.cap-az.com/water/cap-system/water-operations/deliveries/), requested information from CAP (2014 - 2019), and rate schedules available online (http://www.cap-az.com/finances-of-cap/water-rates/).

3. Conceptual Framework

Due to the multiple policy mechanisms, the net impact of the policies on farmers' total water supplies, and in turn planting decisions, is ambiguous. For example, consider a farmer pre-policy with access to a portfolio of water supplies that includes CAP water and groundwater so their total water supply is $W = w^{CAP} + w^{gw}$, where w^j is the farmer's total amount of water from source j. Now consider the "feebate" structure of the Forbearance Program, which lowered the cost for small CAP deliveries through the discount and raised the cost for large deliveries. By increasing the cost of using more CAP water, this mechanism would likely reduce w^{CAP}, and therefore W. Similarly, the Federal Restriction limited the amount of CAP water available, again potentially binding w^{CAP} at a lower level than pre-policy. In contrast, waiving the minimum delivery restriction may have increased W by allowing access to potentially cheaper groundwater and increasing w^{gw}. Under the bundle of policies then, the net effect on total water supplies W is unclear as it depends on the relative magnitude of changes in CAP and groundwater supplies.

Any change in total water supplies could translate into changes in planting decisions through several avenues: 1. the amount of crops planted, 2. the types of crops planted, or 3. the amount of water used per crop. Exactly how these planting margins change will depend both on the direction of the change in total water supplies, as well as changes in the other planting decisions. Additionally, how farmers perceive the permanence of the water supply changes will matter, resulting in either temporary (eg. land fallowing) or permanent (eg. land retirement) changes in crop production. The rest of this section details how water supply changes could be expected to impact the three cropping margins.

First, the amount of land planted is likely positively correlated with changes in total water supplies. The specific response, for example temporary fallowing versus permanent retirement, should be related to farmers' beliefs over the permanence of the water supply change. Hagerty (2021) shows that the extent farmers fallow or retire land in response to water supply reductions depends on the duration of the change in water supplies. This dynamic is also reflected in Akhundjanov et al. (2023) who find long term water transfers away from agriculture lead to reductions in cropped land while Cobourn et al. (2021) and Manning et al. (2017) find increases in fallowing in response to short run water supply shocks. For the analysis in this paper, if total water supplies were reduced it would be expected that farmers would either fallow or retire more land.

Second, farmers may instead plant alternative types of crops in response to changing water supplies. Existing work such as Burlig et al. (2021); Blakeslee et al. (2020); Arellano-Gonzalez and Moore (2020) all find some degree of farmers switching to more drought tolerant crops in response to negative water supply shocks. Hornbeck and Keskin (2014) similarly find increased access to groundwater from the Ogallala Aquifer mitigated the risk of surface water shocks allowing farmers to plant thirstier crops. In the context of this paper, farmers were planting predominantly alfalfa (the highest water use crop) before the policies. If water supplies decreased, farmers may shift plantings towards lower water use barley and wheat instead.

Third, farmers may instead change how much water they apply to a fixed set of crops. For example Drysdale and Hendricks (2018) find this to be an important channel of adapting to reductions in groundwater. This adaptation may be especially relevant in the context of CAP, since one of the primary crops in the region is alfalfa which has a linear yield response to water applied (Shewmaker et al., 2011). If farmers have less water, they may continue to grow relatively high value, water intensive alfalfa but water it less and accept a reduced yield per acre. In contrast, if they have more water they may water alfalfa more than before to achieve greater yields and therefore return.

Lastly, non-linearities in production could lead to interactive dynamics between the three alternative cropping responses. For example, irrigation systems generally irrigate a fixed amount of land and cannot be throttled to fallow just a marginal amount of land. Therefore, if our theoretical farmer experiences a reduction in water supplies, they may fallow more land than the reduction requires due to the non-continuous change dictated by the irrigation technology. In this case, they now have "extra" water which they may use to plant higher water use crops or apply more water to crops on the land that is planted. Other potential non-linearities in production such as minimum water requirements for crop growth or harvesting costs could similarly result in interactive effects on the planting decisions.

4. Data and Methods

To understand the consequences of the policies, I examine the evolution of parcel level outcomes from 2010 through 2021. I focus my main analysis on planting outcomes, but additionally study groundwater access to try and tease out the role of alternative water sources. At the parcel-level, the amount of crops planted, the types of crops planted, and the development of new groundwater wells is available to the econometrician by compiling several data sources. Since these choices are undoubtedly determined in large part by local environmental characteristics, the analysis compares CAP system parcels to non-CAP system parcels that are similar in observed characteristics and located in the Colorado River basin in Southern California and Arizona.[3] In California, parcels are selected from irrigation districts in Riverside and Imperial county while in Arizona parcels are located in Pinal, Maricopa, Pima, La Paz, or Yuma county. See Figure 2 for a map of the Colorado River, CAP canal, and sample counties. Further details on the process of selecting the final sample and data compilation are in Appendix A.1.

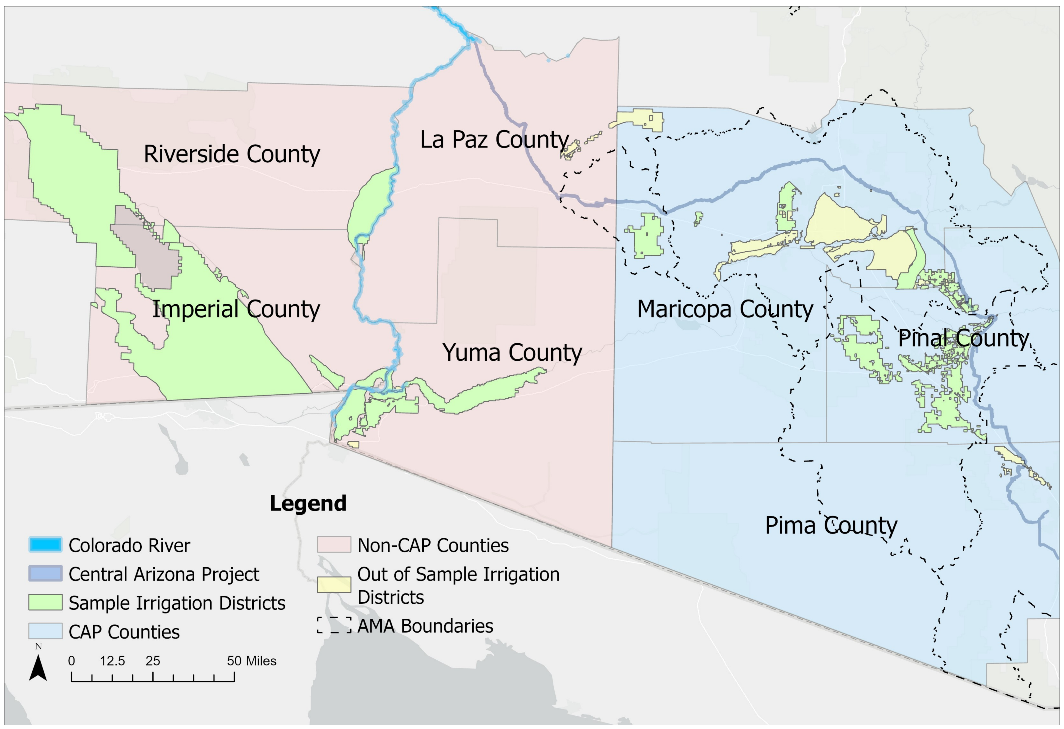
4.1. Data

The aim of the analysis is to understand adaptation to water supply changes at the farm level. I am unable to directly observe the spatial extent of individual farms with publicly available data, so as a second best I use publicly available county assessor property parcels as the level of observation. I use parcels, as opposed to land survey grids like other papers have done, since parcels more narrowly define an area of common land ownership. This remains an imperfect proxy for individual farms though, since multiple parcels may comprise a single farm or parcels with a common owner may be leased to different farmers.

Table A2 of the appendix provides a county level comparison between the universe of parcels used to construct the main analysis sample and farms measured by the National Agricultural Statistics Service's 2012 census. The comparison shows that while there are many more parcels than farms, the median parcel is reasonably similar in size to the median farm and the total amount of cropped land across the two samples is also reasonably similar for most counties. To account for the imperfect proxy, I verify the robustness of the main results to re-weighting parcels by their size, as well as re-weighting parcels by their size scaled so that the total cropped land matches the NASS

[3] I do not include any parcels located within Native American reservations, due to differing water rights.

Figure 2: Map of Study Region



Map of sample area. Irrigation districts in blue shaded counties are eligible to use water from the Central Arizona Project, though only those in bright green are observed as having received a delivery at some point since 2010. Sample irrigation districts in the red counties are observed as having received deliveries from the Colorado River since 2010.

measurements.[4] These re-weighting exercises aim to understand the treatment effect for a unit of land in the sample and a unit of land in the population of interest respectively. The results are shown in Table A4, and are similar to those of the main analysis.

Crop data

Estimating cropping behavior is common among the existing literature, in part because a wide array of detailed data is readily available. This analysis relies on land coverage data from the National Agricultural Statistics Service's Cropland Data Layer (CDL). The data is derived from satellite imaging and provides annual, spatial data on acreage and crop type planted. By overlaying parcel boundaries, the CDL data are used to construct annualized data on the share of a parcel that is left fallow or cropped, as well as the share of planted land that is occupied by different types of crops. I define fallow land as land that is recorded in the CDL as being fallow and cropped land as land that is identified in the CDL as having any type of crop. These two measures can be thought of as the extensive margin of planting, since they reflect how much is planted.

To understand the intensive margin of what types of crops are planted, I use the granularity provided by the CDL to focus on specific crops. Specifically, I measure the change in the share of total cropped land that a specific crop occupies. Because examining every crop identified in the CDL would be excessive, I narrow the crop specific analysis to the five most common crops in the treated counties: alfalfa, cotton, barley, wheat, and corn. These five crops make up around 90% of the crops in the treated counties before 2015, with alfalfa being the most common, as shown in Table A1.

To construct an estimate of the water intensity of planting for a parcel, I combine the CDL data on area planted and crop type with estimates of crop specific water needs in Arizona's Salt River Valley reported by Erie et al. (1981)[5]. The report contains crop specific consumptive water use over

[4]The scalar used is equal to the respective county's census measured cropland divided by the county's total cropland in the parcel data.

[5]The water needs of crops are highly dependent on external environmental factors as well as crop characteristics. For example, Hanson et al. (2008) found that alfalfa grown in Imperial Valley in southern California required 76 inches of water, while in Scott Valley in northern California alfalfa only required 33 inches of water. While Erie et al. (1981) is older and potentially outdated, it has the benefit of uniformly measuring water needs

a growing season, measured in inches. For each parcel in a given year, I estimate an index value that is the average of the crop specific water needs, weighted by the share of land in the parcel that is occupied by the crop. Formally, denoting water intensity of parcel p in period t as $i_{p,t}$,

$$i_{p,t} = \frac{\sum_c \text{consumptive water use}_c \cdot \text{acres}_{c,p,t}}{\text{total acres}_{p,t}} \tag{1}$$

This measure is bounded between 0 and 74.3, as 74.3 inches is the seasonal consumptive water use of alfalfa which is the most water intense of the five main crops c, and is interpreted as an estimate of the parcel level mean acre feet of water (converted to inches) used per acre. Alfalfa and cotton are more water intensive than barley, corn and wheat, and will be denoted in the remainder of this paper as "high water use crops" for brevity.

For each of the five main crops observed in the CDL, I collect annual state-level average yield per acre and price received per unit of yield from the National Agricultural Statistics Service's Annual Statistical Bulletins for California and Arizona.[6] I use this data to construct annual measures of price received per acre for each of the five main crops which I use for supplemental analyses.

Evapotranspiration data

To better understand the intensive margin of how much water is applied to a given area of crops, I would ideally directly observe how much water is used to irrigate per acre. This is unobserved, so I instead proxy for this outcome using annual cumulative evapotranspiration (ET) measured by MODIS aboard the Terra satellite, accessed via NASA's EarthData portal. This data is available annually at a spatial resolution of 500 meters. ET measures the amount of water moving from the Earth's surface to the atmosphere through either evaporation or plant transpiration. Conditional on temperature and precipitation, a higher ET value implies higher transpiration, and therefore that the plants are consuming more water. If farmers are applying less water

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in central Arizona for all of the sample crops. The Salt River Valley overlaps Maricopa, Pinal, and Gila counties.

[6]Arizona: https://www.nass.usda.gov/Statistics_by_State/Arizona/Publications/Annual_Statistical_Bulletin/index.php
California: https://www.nass.usda.gov/Statistics_by_State/California/Publications/Annual_Statistical_Reviews/index.php

to a given amount of a specific crop, we would expect the ET value to be lower. I compile the MODIS data to get an annual, parcel-level average of cumulative ET. Note that this aggregate measure captures variation in the amount of water applied, the types of crops planted, and the amount of crops planted.

Groundwater data

In addition to changing how water is used, the policy bundle may induce farmers to change where they are getting their water from. Direct, parcel level measurements of water used from alternative sources is unavailable, so I instead examine investment in new agricultural groundwater wells and variation in the cropping decisions by estimated groundwater costs. For digging new wells, in both California and Arizona entities must submit a well drilling application, though the governing authority differs by location. In Arizona, well application data for the whole state is compiled and made publicly available through the Arizona Department of Water Resources.[7] In California, well permits are typically issued by counties and only Riverside county records of these permit applications is publicly available[8]. These data sets for Arizona and Riverside county contain the wells' coordinates, permit application dates, and a categorization for the type of well. I remove wells that are classified as being for environmental monitoring, aquifer recharge, other special uses, or specifically non-irrigation use (i.e. exempt). I then use the date of permit application and coordinates to identify new wells at the parcel level to measure changes in groundwater investment and proxy for alternative water supplies. I focus on this margin of change, rather than a measure of completed groundwater wells, both due to data availability and because it more accurately reflects demand for groundwater.

While wells are observable, the cost of groundwater extraction is not. As discussed in Burlig et al. (2021), groundwater costs are a function of the localized groundwater depth, electricity rates, and pump characteristics. To approximate groundwater pumping costs I use publicly available data from the California Natural Resources Agency[9] and the Arizona Department of

[7] Registry of Wells in Arizona: https://azwatermaps.azwater.gov/wellreg

[8] Department of Environmental Health Water Well Finder: https://countyofriverside.maps.arcgis.com/apps/webappviewer/index.html?id=52a006e2361d4819bc0dc711b53f5533

[9] https://data.cnra.ca.gov/dataset/periodic-groundwater-level-measurements

Water Resources[10] containing depth to groundwater measurements for observation wells across the sample area over time, and marginal electricity rates for irrigation pumping manually collected from the relevant utility providers for the year 2023. For each year, I interpolate a raster file of groundwater depths using inverse distance weighting of the observed points in the given year. I then link parcels to the relevant interpolated groundwater measure multiplied by the marginal electricity price of the relevant utility provider and a constant.[11] The constant is the ratio of the average kWh per AF conversion factor to average operating pump efficiency estimated in Burlig et al. (2021), since these relevant pump characteristics are unavailable in my sample.

See Section Appendix A.1 for more details on the full data compilation process, and Section Appendix A.2 for sources of supplementary data sets.

4.2. Empirical estimation specifications

The main regression specification I employ uses a difference-in-differences framework comparing non-CAP parcels to CAP parcels before and after 2015, when the initial reduction in water deliveries occurred. As discussed in Section 2.1, CAP itself defines its service area as encompassing 15 irrigation districts in three counties. However, the exact irrigation districts served in a given year depends on needs and supplies, with three districts never receiving deliveries from 2010 through 2021. I therefore define a parcel as being in CAP if it is in one of the 12 irrigation districts that have received CAP water at some point since 2010. I omit parcels in the three remaining districts from the main analysis, since they are both not treated (as they did not experience a shock to water supplies) and potentially invalid controls as they may be subject to unobserved shocks that are indirectly due to the changes in CAP water.

I similarly define the set of non-CAP parcels to be those that are in one of the 15 irrigation districts in a control county, but that is observed as having received a delivery from the Colorado River since 2010 (11 districts).[12] I restrict controls to be in an irrigation district so that they face a similar structure for water access as the treatment group. From all irrigation districts

[10] https://new.azwater.gov/gis

[11] I link parcels instead of wells since having a well is endogenous to groundwater costs.

[12] This information is from the US Bureau of Reclamation Lower Colorado River Water Accounting Reports. https://www.usbr.gov/lc/region/g4000/wtracct.html

in the four control counties, I limit to those that are observed as receiving water from the Colorado River so that I am better able to observe potential confounding from changes in the control group water supplies.

A concern is that control irrigation districts may also respond to changing river conditions and reduce their total river deliveries or reallocate water internally, making them invalid controls. Figure A3 shows that the four largest control irrigation districts (which contain about 75% of the analysis sample control group) did not reduce their deliveries over the sample time frame at all. I am unable to observe reallocation of water within a district though,[13] so I include a leave-one-out robustness check (Figure A4). This check allows me to verify that no individual contaminated control irrigation district is driving my main results, as the leave-one-out coefficients are all within the 95% confidence intervals of the main analysis coefficients. I also repeat the main analyses with alternative definitions of control units in Table 7, with the results discussed in Section 5.5.

For each outcome of interest y for parcel p in period t, I estimate

$$\begin{aligned} y_{p,t} =& \alpha + \lambda_1 \mathbb{1}(\text{After 2015}) + \lambda_2 \mathbb{1}(\text{In CAP}) + \beta_1 \mathbb{1}(\text{After 2015})\mathbb{1}(\text{In CAP}) + \\ & \delta_p + \delta_t + \gamma X_{p,t} + \varepsilon_{p,t} \end{aligned} \tag{2}$$

where δ_p captures either an irrigation district or parcel-level fixed effect and δ_t is a year fixed effect. When using irrigation district level fixed effects, the vector $X_{p,t}$ measures the parcel-level environmental features: elevation, soil hydrologic group[14], mean temperature between June and October of year t, accumulated precipitation and its square from June to October in year t, depth to groundwater in year t, and parcel size. Only temperature, precipitation, and groundwater depth vary with time, the rest are defined by their values in the year 2020. Additionally, I include pre-2015 average planting decisions for the share of the parcel left fallow, share of the parcel with any crops, and the share of the five main crops planted that are high water use crops. For the parcel-level fixed effect specification, $X_{p,t}$ contains only the temperature, precipitation, and groundwater depth controls since all other covariates are time invariant. For all specifications standard errors are

[13] This could be groundwater banking, transfers of water to environmental services, or changes in fallowing and water efficiency programs.

[14] The soil hydrologic group is an index of the rate that water infiltrates a soil.

clustered at the irrigation district level, since irrigation districts coordinate the water deliveries, and parcels outside of an irrigation district are dropped. My main sample uses parcels in 23 irrigation districts of varying sizes, so I use wild bootstrapped standard errors to accommodate the small number of effective clusters (Lee and Steigerwald, 2018).[15]

For the main analyses, I consider the combination of the Forbearance Program and Federal Restriction as a larger policy bundle since they were equally effective at reducing surface water deliveries. It is interesting though to use the differences in the policy implementations ("feebate" versus quantity restriction) to begin a discussion on effect heterogeneity in outcomes under different implementations. To do this, I expand the main analyses to an event-study framework following the specification

$$y_{p,t} = \alpha + \delta_t + \delta_p + \sum_{j=1}^{11} \beta_j \mathbb{1}(t = j)\mathbb{1}(\text{In CAP}) + \gamma X_{p,t} + \varepsilon_{p,t} \qquad (3)$$

where the vector of climate controls is unchanged, δ_t measures the year fixed effect and δ_p reflects a parcel-level fixed effect. While a perfect comparison of the two policy implementation strategies is difficult in this context due to the sequential nature of the policies and the continued removal of the delivery minimum restriction, the setting used for this analysis provides a unique opportunity to gain a better understanding of trade-offs between alternative policy strategies. To my knowledge, no other paper has been able to directly compare outcomes of water regulation policies where the same group of farmers were exposed to two policies that resulted in the same decline in surface water with the only difference being the way the policies were implemented.

4.3. Identification

The underlying assumption for the claim of exogeneity to hold is that the historic assignment of junior rights to CAP water in 2004 influences present changes in crop production or investment only through the mandatory reduction of water use in times of shortage and the threat of this reduction.

[15] Irrigation districts coordinating water deliveries means that access to river water is assigned at the irrigation district level (clustered treatment assignment). Additionally, as shown in Section 5 there is treatment effect heterogeneity. Following Abadie et al. (2017) I cluster standard errors.

Note that before 2020, there had never been a mandatory reduction in deliveries. While it is likely that the junior rights standing is related to level differences in present production, it is less likely to be related to differential changes in present production. Due to the aggregated, spatial nature of CAP water rights assignment though, there are several possible ways in which this assumption might fail.

The first potential avenue for failure is confounding through localized shocks, such as a climate shock or crop demand shock, which disproportionately affects parcels in the CAP or non-CAP irrigation districts. To tighten up the observed similarities of the control parcels to CAP parcels, I use propensity score matching to select a subset of parcels from the non-CAP counties to act as controls. For each parcel in the full sample of parcels, I estimate a propensity score as the linear function

$$\mathbb{P}(\text{In CAP}) = \alpha + \lambda_1 \text{Planting}_p + \lambda_2 \text{Water trends}_p + \lambda_3 \text{Environment}_p + \varepsilon_p \tag{4}$$

The vector $Planting_p$ includes the average of planting decisions from 2010 through 2014, with the share of the parcel left fallow, the share of the parcel with any crop, the estimated water intensity index, and of the five main crops planted the share that are high water use. I explicitly control for parcel-level trends in water intensity with $Water\ trends_p$ which contains the estimated coefficients from parcel-specific regressions of the water intensity per acre constructed from equation 1 on year, and the depth to groundwater (winsorized at 0.5 and 99.5 percentiles) on year for 2010-2014. Lastly, I include controls for some key environmental characteristics: average temperature from 2010-2014, parcel size, and soil quality[16]. All continuous variables used to predict the propensity score are converted to standard normal distributions.

I then use nearest neighbor matching with replacement on the estimated propensity scores, selecting for each treated parcel up to three control parcels that have a propensity score within 0.01 of the treated parcel's propensity score. The observable characteristics of the unselected non-CAP parcels, selected non-CAP parcels, and CAP parcels are shown in Table 2. Since the matched non-CAP parcels are generally more similar on observables than the unmatched parcels, my preferred specification uses the matched sample for

[16] I do not include parcel elevation or precipitation due to lack of common support with the pool of control observations.

all of my main analyses. Table A5 in the Appendix presents the main results estimated on the unmatched sample and a sample matched using coarsened exact matching on the same set of variables. I also show event studies for the unmatched sample in Figure A5. The main takeaways are largely unchanged under the alternative matching procedures. The unmatched sample is quite different in the estimated net water intensity effect, due to differences in the estimated effect on high water use crops. This suggests that the matching is important for homogenizing the types of crops planted across treated and control groups (see Table 2).

In addition to climate or demand shocks, unobserved local policies may be a problem. These policies could be fallowing programs implemented by irrigation districts, like discussed above, or policies from other water management agencies. Of particular note in Arizona, groundwater in specific areas called Active Management Areas (AMAs) is subject to additional regulation and monitoring. It would be a concern for identification if in response to changing river conditions the AMAs also implement changes that affect overlying parcels' water supplies, as all of the treated parcels are in an AMA (see Figure 2). To verify that unobserved policies of the AMA are not contributing to my results, I repeat my main analysis using parcels that are in the AMA boundaries but not in the treated districts as a control group. The results are shown in Table 7 and discussed in Section 5.5.

A second source of potential confounding stems from differences in irrigation technology due to variation in water rights (Smith, 2021). Differential irrigation could lead to differential changes in soil salinity since more water efficient irrigation systems can lead to a build up of harmful salinity that would otherwise be "washed out" of the soil by less efficient irrigation (Morford, 2014). Using aggregate data from the 2018 Irrigation and Water Management Survey performed by the USDA National Agricultural Statistics Service, farms in California are much more likely to use drip, trickle, or low-flow micro sprinklers (around 65%) than farms in Arizona (15%).[17] Since more efficient water use would imply a faster accumulation of salts in the soil, the higher uptake of drip irrigation in the control counties could increase the average soil salinity for non-CAP users, biasing the estimated

[17]Gravity or sprinkler systems are the alternative to drip irrigation systems. They are considered to be inefficient compared to drip systems, when measuring efficiency as the share of applied water used by the crop (Frisvold et al., 2018).

Table 2: Average Parcel Characteristics

	Nonmatched Controls	Matched Controls	Treated	Difference
Panel A: Environmental characteristics				
Acres	43.74	49.04	30.89	-18.14
	(0.52)	(0.26)	(0.23)	(0.37)
Temperature (C)	23.59	29.65	29.90	0.25
	(0.01)	(0.01)	(0.00)	(0.01)
Elevation (m)	212.17	40.79	395.92	355.13
	(0.41)	(0.15)	(0.12)	(0.20)
Precipitation (mm)	18.28	24.01	79.74	55.73
	(0.03)	(0.07)	(0.11)	(0.16)
Soil quality	2.53	2.32	2.51	0.19
	(0.00)	(0.00)	(0.00)	(0.00)
Cost per KWh ($)	0.09	0.09	0.08	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Depth to groundwater	117.61	115.38	198.19	82.81
	(0.14)	(0.24)	(0.23)	(0.37)
Panel B: Decision characteristics				
Share of parcel that is agriculture	0.49	0.65	0.57	-0.08
	(0.00)	(0.00)	(0.00)	(0.00)
Share of parcel that is developed	0.18	0.13	0.26	0.14
	(0.00)	(0.00)	(0.00)	(0.00)
Water intensity index	9.17	23.66	21.16	-2.50
	(0.04)	(0.14)	(0.08)	(0.15)
Share of parcel that is left fallow	0.08	0.14	0.19	0.05
	(0.00)	(0.00)	(0.00)	(0.00)
Share of planted land with high water use crops	0.35	0.84	0.86	0.03
	(0.00)	(0.00)	(0.00)	(0.00)
Labor index	0.72	2.51	2.27	-0.24
	(0.00)	(0.01)	(0.01)	(0.02)
Price index	223.99	551.11	413.32	-137.79
	(1.01)	(3.67)	(3.22)	(5.35)
Number of wells applied for since 2010	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Number of parcels	26,372	7,778	15,471	
Parcel-year observations	316,464	93,336	185,652	

Table presents average parcel characteristics by treatment groups, with standard deviations shown in parentheses. "Nonmatched Controls" is the set of parcels that are eligible controls but not matched to a treated parcel while "Matched Controls" are matched to a treated parcel. "Difference" contains the level difference between treatment and the matched controls. Panel A presents exogenous parcel features, averaged over 2010-2021. Soil quality is a categorical variable measuring water infiltration rate, where a value of 1 reflects high infiltration while 4 and higher reflects low infiltration. Cost per KWh measures the average electric price of energy used for irrigation. Panel B presents potentially policy varying outcomes, averaged from 2010-2014. Agriculture land is defined as planted with any crop or fallow land. The labor and price index measures are constructed identical to equation 1, except using the hours of labor (Estimates of hourly inputs for crops from Texas A&M AgriLife Extension crop budgets for 2021. https://agecoext.tamu.edu/resources/crop-livestock-budgets/) and average price received for each crop rather than water needs.

coefficients of interest towards zero. More detailed data on parcel level irrigation technology is unavailable.

Lastly, a potential concern with the identification strategy is that the reduction in surface water, while only directly affecting CAP parcels, could have had spillover effects to the non-CAP parcels. The most likely way this could happen is if non-CAP farmers were aware that the production of CAP farmers would be reduced due to water shortages and increased their own production in response, biasing results away from zero. The most common crops grown in the sample area are cotton and alfalfa, both of which are produced across the US and exported abroad. For alfalfa, in 2010 the US produced about 145 million tons with less than 2% of that total coming from Arizona. Similarly for cotton, Arizona in total produced about 3.5% of the total US production (USDA National Agricultural Statistics Service, 2017). Since production by CAP farmers is relatively small in the total market, it seems unlikely that any changes in CAP production would result in changes in other producers' behavior.

5. Empirical Results

5.1. Estimated water per acre

I start by examining how the reduction in surface water deliveries starting in 2015 impacted the overall water intensity of plantings on a parcel. To do so, I use the constructed estimate of water intensity per acre, from equation 1, that combines both how much farmers planted with the types of crops being planted. The results of this analysis are shown in Table 3, with the matched sample used for analysis in columns 1 through 4 and the full sample used for column 5. From left to right, the models include more controls starting with the most basic specification without controls in column 1 to the most rigorous specification in column 4 with year and parcel fixed effects, as well as controls for time-varying parcel characteristics. Across the alternative specifications used with the matched sample, the reduction in surface water deliveries is associated with a reduction in average water intensity of plantings per acre around 1 inch, that is not statistically different from zero. However, I am unable to rule out potentially economically significant effects, since the 95% confidence interval includes reductions of about 5 inches. Extending the logic from the framework presented in Section 3, the small, insignificant coefficient implies there was almost no change in W^* due to the policy bundles, even though w^{CAP} declined. This implies then that either w^{gw} or w^{sw} increased

Table 3: Effect of Policies on Estimated Water Per Acre

	(1)	(2)	(3)	(4)	(5)
Indicator for 2015 or later	-1.619				
	(1.478)				
In CAP county	-4.629				
	(4.507)				
CAP $\times$ Post 2015	-0.868	-0.868	-1.303	-0.892	-4.469***
	(1.604)	(1.604)	(1.710)	(1.446)	(0.992)
Pre-2015 treated average	21.159	21.159	21.159	21.159	21.159
Fixed effect	None	ID, Year	ID, Year	Parcel, Year	Parcel, Year
Climate controls	No	No	Yes	Yes	Yes
Obs	736,056	736,056	733,872	733,872	393,444
R-Squared	0.008	0.125	0.570	0.669	0.616

Table presents the main specification for the outcome of the constructed water intensity index (equation 1). *CAP* is an indicator for a parcel in an irrigation district that uses CAP water. *Post 2015* is an indicator for the observation being in 2015-2021. Column 1 contains no controls, while column 2 introduces an irrigation district fixed effect and a year fixed effect. Climate controls are included in columns 3. A parcel fixed effect replaces the irrigation district fixed effect in column 4, and only the time varying climate controls are included. Column 5 repeats the specification from column 4 for the sample including all potential control parcels. Matched controls are weighted by the number of treated parcels they are matched to in columns 1 to 4. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

with removal of the minimum delivery, or that water is not the binding constraint for production.

5.2. Change in water use

Farmers may change their planting decisions along three margins: the amount of crops planted, the types of crops planted, and the amount of water used per crop. The first two outcomes are directly observable in the CDL data, and Table 4 presents the coefficient estimates for these outcomes under the difference-in-differences analysis framework. Looking first at the amount of crops planted, columns 1 through 3 suggest that farmers on average permanently retire land with the reductions in surface water, as the share of the parcel that is cropped falls 8 percentage points while the share of the parcel that is left fallow increases by 4 percentage points, though the point estimate is statistically insignificant. This would suggest that farmers view the reductions in surface water as a long term change, since they are not maintaining the not planted land for future use. Hagerty (2021) also finds that long run changes in water supplies leads to retirement of land as opposed to fallowing. Column 3 presents suggestive evidence that farmers are reallocating their land away from agriculture and toward urban development, however due to data limitations of the CDL this analysis is highly subject to measurement error and requires further investigation.

Columns 4 through 8 present the changes in the crop-specific share of total planted land (crop specific event studies are shown in Figure A6). Column 4 shows that alfalfa was the most commonly planted crop before 2015 for CAP parcels, with about 65% of the planted land being occupied by alfalfa, and post-2015 there was a statistically significant increase in area occupied by 8.5 percentage points. Cotton, the other most water intensive crop, experienced negligible changes in the relative amount planted. In contrast the low water use crops barley, wheat and corn, which were also some of the least popular (of the main five) before 2015, were planted even less after 2015, with the share of planted land occupied by barley reducing by 4 percentage points. In total, columns 4 through 8 show farmers do not appear to switch to lower water use crops in response to the policies but instead concentrate plantings towards alfalfa. At first blush this is surprising since alfalfa is a relatively high water use crop, however alfalfa also tolerates deficit irrigation which could explain the observed increase. If the policies reduced farmers' total water supplies, they may plant more alfalfa but apply less water in total. This approach would allow farmers to still get the higher returns from alfalfa than other, low water use crops but they would receive a smaller total yield.

Table 4: Effect of Policies on Cropping Decisions

	(1) Cropped Land	(2) Fallowed Land	(3) Developed Land	(4) Alfalfa	(5) Cotton	(6) Barley	(7) Wheat	(8) Corn
CAP × Post 2015	-0.081**	0.041	0.076*	0.085***	-0.010	-0.041***	0.007	-0.005
	(0.024)	(0.027)	(0.027)	(0.022)	(0.014)	(0.008)	(0.007)	(0.005)
Pre-2015 treated average	.406	.192	.237	.648	.142	.056	.022	.037
Sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample
Fixed effect	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	733,872	733,872	733,872	600,503	600,503	600,503	600,503	600,503
R-Squared	0.752	0.517	0.858	0.504	0.416	0.268	0.182	0.261

Table presents the main specification for the outcomes of the share of a parcel left fallow (1), cropped (2), or developed (3) and the share of total planted land occupied by specific crops (4-8). *CAP × Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Without parcel level measures of the water applied per acre it is impossible to directly test this option. As a second best, I use parcel level average ET which is indicative of the water available to plants. I repeat my main regression specification (equation 2) on the natural log of parcel average cumulative ET in Table 5. I find that after 2015 the average ET value for a CAP parcel increased by around 8 percent. Tables 3 and 4 show changes in both the amount and types of crops planted, both of which could impact ET and hide reductions in water applied conditional on crop type and amount. To test for this, column 5 of Table 5 controls for the constructed water intensity index from equation 1, which captures both the amount of land planted and the water requirements of the crops planted. The idea is that the residual variation in ET, conditional on plantings as captured by the water intensity index and temperature and precipitation, is entirely due to changes in water applied. The point estimate of this analysis is very similar to that of column 4, which suggests that conditional on the expected water needs of the crops planted, farmers did not meaningfully reduce the amount of water used per crop, instead increasing water appplication.

This finding directly contrasts with the theory that farmers experienced a reduction in water supplies and increased alfalfa plantings to benefit from deficit irrigation. The analysis faces limitations though, as ET is subject to many unobserved factors (eg. solar irradiance, precipitation, etc) and I am unable to observe parcel specific yields. As a supplemental analysis, I compile county specific yields per acre for four of the five main crops[18] over time from the NASS Annual Statistical Bulletins for California and Arizona. Table A6 in the Appendix shows that there is little difference in the change in yield per acre between the treated and control counties. While a constrast with the estimated increase in ET, this further supports the results that farmers are not significantly reducing the amount of water used per crop in the face of surface water reductions.

The bundle of policies reduced surface water deliveries by approximately 35% each year from 2015 through 2021. If there was a direct reduction in total water supply such that farmers saw a one-to-one reduction in water use per acre, a 35% reduction over the baseline 21.2 inches per acre would result in an average decline of 7.4 inches. Instead, the data shows that there was little change in total water intensity of plantings. While between 2015

[18]Data on corn yields is unavailable after 2008.

Table 5: Effect of Policies on Log of ET

	(1)	(2)	(3)	(4)	(5)
Indicator for 2015 or later	-0.047				
	(0.028)				
In CAP county	-1.230***				
	(0.299)				
CAP $\times$ Post 2015	0.064	0.064	0.090**	0.079*	0.084**
	(0.042)	(0.042)	(0.037)	(0.036)	(0.033)
Pre-2015 treated average	1.729	1.729	1.729	1.729	1.729
Fixed effect	None	ID, Year	ID, Year	Parcel, Year	Parcel, Year
Climate controls	No	No	Yes	Yes	Yes
Obs	672,131	672,131	670,775	670,763	670,763
R-Squared	0.118	0.325	0.562	0.972	0.975

Table presents the main specification for the outcome of the natural log of parcel cumulative ET. *CAP* $\times$ *Post 2015* is the estimate of β_1 from equation 2. Column 1 contains no controls, while column 2 introduces an irrigation district fixed effect and a year fixed effect. Climate controls are included in columns 3. A parcel fixed effect replaces the irrigation district fixed effect in column 4, and only the time varying climate controls are included. Column 5 introduces a control for the water intensity index. Matched controls are weighted by the number of treated parcels they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

and 2021 farmers on average reduced the relative amount of land planted, they also planted more alfalfa and potentially irrigated more. This finding is consistent with the theory presented by Manning et al. (2017), where "the optimal allocation of scarce water involves concentration of the water on fewer acres in order to maintain high yields while incurring lower harvest costs". The concentration of water onto smaller areas of land could also be consistent with production non-linearity as discussed in Section 3.

5.3. Effect dynamics

As discussed in Section 2, an interesting aspect of the setting of this analysis is that the consistent reduction in surface water deliveries over time is actually the result of two sequential policies. The first policy, announced first in 2014, offered discounts on CAP water conditional on reducing deliveries. The discount structure of the Forbearance Program was then completely replaced by the Federal Restriction, announced in 2019, which instituted a limit on the total amount of water that could be delivered via CAP. Both policies waived the need to use the full allotment of CAP water before other sources.

Expanding the main analyses with the matched sample to the event study specification outlined in equation 3 reveals interesting effect dynamics, as shown in Figure 3. With the implementation of the Forbearance Program in 2015, farmers increased the water intensity of their plantings between 2015 and 2018. This appears to be due to a combination of planting more water intensive crops and planting slightly more land (though the pretrends for fallowing are noisy). Additionally, there is a stark, large increase in ET starting in 2015, though again the pretrends are also somewhat noisy.

As discussed in Section 2.2, the Forbearance Program incentives evolved over time, with the dollar value of the available discount decreasing with time between 2015 and 2019, though the 2016 removal of the minimum delivery was permanent. The volume of deliveries over this time declined and then stabilized, while the estimated water intensity increased up until 2018. This behavior implies that the main driver of delivery reductions under the Forbearance Program was the Ag Forbearance 3 program, which waived the delivery minimum indefinitely, since delivery volume and planting choices did not respond to incentive reduction.

In 2019 there was a sudden decrease in the relative water intensity compared to the counterfactual due to a sudden increase in the amount of land left fallow and a reduction in the amount of land planted. Plotting the share

Figure 3: Policy Effect Dynamics

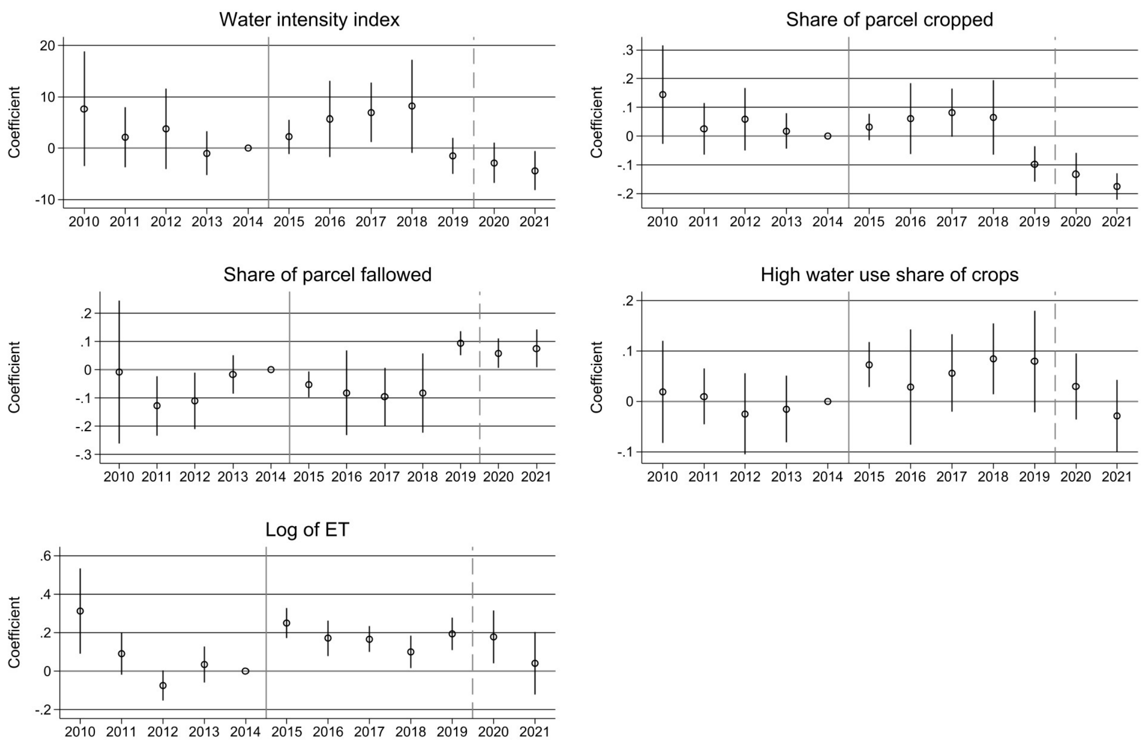

Figure plots the coefficients from the interaction of an indicator for CAP service and the year of the observation. Vertical lines denote the start of the policies, note that both policies were announced the year before implementation. The omitted interaction is for the year 2014. All specifications include climate controls and year and parcel fixed effects, and the ET analysis controls for the water intensity index. Matched controls are weighted by the number of treated parcels in the subsample that they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

of land left fallow and cropped separately over time (Appendix Figure A7) for the weighted matched sample shows that the sudden divergence in 2019 is due to a shock experienced by irrigation districts in the control group that greatly reduced control group fallowing and increased planting. The treated group is unaffected by this shock, and experienced limited changes in fallowing over time. This sudden change in control group planting does not technically violate the difference-in-differences assumptions, and instead reflects a change that the treated group *should* have experienced. It does, however, make separating the effect of the distinct policies difficult, and is potentially concerning for the external validity of the main analyses. Table A7 in the Appendix re-estimates the main results on a subsample cutting off 2019-2021. The main analyses includes 2019 to 2021 though, since the lack of adjustment in 2019 is potentially an important impact of the reductions in deliveries: treated farmers may have been constrained by the available water supplies and unable to increase production as they would have in absence of the policy.

Even with the sudden change in control group planting between 2018 and 2019, it is still informative to examine the difference in outcomes between 2019 (the last year of the Forbearance Program) and 2020-2021. Figure 3 shows that during this narrower time window there was little change in fallowed area but a gradual reduction in cropped area. There was a similar reduction in the amount of crops that are high water use, though the coefficient confidence intervals overlap. For none of the outcomes shown in Figure 3 was there a sharp change with the policy transition. Overall, it seems that the two policies largely had similar effects. This makes sense - if the Forbearance Program worked primarily through waiving the delivery minimum, then removing the financial incentives should have had little impact. Additionally, since the voluntary reductions in deliveries under the Forbearance Program equated to the required reductions under the Federal Restriction, and the minimum delivery continued to be waived, there should be little change in the net amount of water available to end users.

5.4. Alternative water sources

The substitution of Colorado River water with alternative sources is a common theme among the irrigation district notices to consumers and the agreements that comprise the Forbearance Program, in part because for some CAP users groundwater is cheaper than CAP water (Maricopa-Stanfield Irrigation and Drainage District, 2021b; San Carlos Irrigation and Drainage

District, 2022; Central Arizona Project, 2016b). To explore the extent that farmers shift to alternative sources, I would ideally be able to observe exactly how much water farmers use from each source. This granularity of data is unavailable, so as a second best I approximate access to alternative water sources, specifically groundwater, with measures of applications for groundwater well permits and a constructed estimate of groundwater extraction costs.

I first examine the outcome of application for permits to drill new groundwater wells. Regulation around drilling wells is very location specific, so that in some irrigation districts farmers are able to drill and use private wells while for others the district drills and maintains the wells. To accommodate this variation, I estimate equation 2 for the outcomes of an indicator for any new well applications submitted for both the sample of parcels and a collapsed sample aggregated to the irrigation district level. For the irrigation district level analysis I also estimate the effect on the number of applications, conditional on applying. Column 1 of Table 6 shows there is potentially an increase in well drilling permit applications at the parcel level, though this effect is statistically indistinguishable from zero. While the coefficient magnitude is small, about 0.6 applications more per 1,000 parcels, it is relatively large compared to the pre-2015 average application rate of 0.4 applications per 1,000 parcels. At the irrigation district level column 2 shows an 8 percentage point increase in the probability of applying to drill a new well, a 62% increase over the base rate of 13 percent. Conditional on applying for a well, the aggregate of farms in CAP districts apply for less wells than the aggregate of farms in control irrigation districts, though the effect is statistically insignificant and estimated on an especially small sample.

The increase in groundwater well drilling applications in CAP districts aligns with anecdotal evidence that districts are supplying farmers with more groundwater and less surface water. However, two drawbacks with this analysis are that drilling wells is a rare event and it captures groundwater investment at an extensive margin only. Instead of drilling new wells districts may rehabilitate existing wells or new wells that are being drilled may be deeper and larger than their counterfactual counter parts (Migoya, 2023), characteristics that are not consistently available in the data.

As an alternative, I examine heterogeneity in cropping decisions by estimated groundwater costs. The goal of this analysis is to use differential impacts by groundwater access, proxied by estimated costs, to understand the role of groundwater in supplementing forgone surface water supplies.

Table 6: Effect of Policies on Well Drilling Permits

	Parcel	Irrigation district	
	New well	New well	Number of wells
CAP $\times$ Post 2015	0.0006	0.0837*	-0.0904
	(0.0003)	(0.0435)	(1.0540)
Pre-2015 treated average	.0004	.13	1.967
Fixed effect	Parcel, Year	ID, Year	ID, Year
Climate controls	Yes	No	No
Obs	733,872	720	151

Table presents the main specification for the outcome of the probability of applying to drill a new well and the number of applications, conditional on applying. *CAP* $\times$ *Post 2015* is the estimate of β_1 from equation 2. Column 1 is at the parcel level of analysis and includes parcel and year fixed effects and parcel level climate controls. Columns 2 and 3 are at the irrigation district level and contain irrigation district and year fixed effects only. Matched controls for column 1 are weighted by the number of treated parcels they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

I estimate groundwater costs following Burlig et al. (2021), constructing a measure of dollars per acre foot that is a function of depth to groundwater and local electricity costs for irrigation pumping. I then categorize parcels into low, medium, and high groundwater cost terciles based on the distribution of parcels' average groundwater costs pre-2015. I re-estimate the main crop analyses on subsamples broken apart by tercile of electricity cost. For each subsample, I select from the full sample of treated and potential control parcels only those that are within the given tercile, and then rerun the matching process on this smaller group to get the final subsample of parcels. I use this subsampling approach as opposed to interacting the difference-in-differences coefficients with tercile to account for the matched structure of the main analysis sample.

The results of this analysis for the bottom and top terciles are shown in Figure 4, where the coefficients are interpreted as the subsample specific average effect relative to 2014. While the pretrends are relatively noisy, it is interesting to note some consistent trends across the subsample coefficient point estimates. After 2015, those with high groundwater costs consistently planted less and fallowed more, relatively, compared to those with low costs. This dynamic contributes to differences in the estimated water intensity, with high groundwater cost parcels seeing no increase in intensity from 2015 through 2018, and a larger decrease from 2019 to 2021. In total, Figure 4 highlights significant heterogeneity in the point estimates by estimated groundwater costs, with parcels with high groundwater costs being more adversely affected. This aligns with Smith and Edwards (2021) and Tsur and Tomasi (1991), who document that access to groundwater provides resiliency to other water supply shocks. This finding also aligns with the conceptual framework, as those with higher groundwater costs are less able to take advantage of the removal of the minimum delivery restriction, so their total water supplies are more likely to decrease given a reduction in surface water supplies.

To further explore groundwater substitution, I supplement my main analysis with data from the Arizona Department of Water Resources on water use in AMAs. This data contains withdrawal amount, year, AMA, and irrigation district for anonymized agricultural water users. Figure 5 plots the total amount of groundwater and other surface water supplies withdrawn by users in the treated CAP irrigation districts of the main analysis. Notably there is an increase in groundwater withdrawals, with an increase of 125,085 AF between 2014 and 2018, and limited change in surface water withdrawals. Comparing these to the 192,000 AF decline in Colorado River deliveries suggests that groundwater is the main source of substitute water supplies. This is further supported by running a basic event study with out any controls comparing users in the treated districts to users in other irrigation districts in the AMA areas. This analysis, shown in Figure A8 of the appendix, shows that the increase in groundwater withdrawals was specific to the treated group. It is interesting to also note that there is a relative decline in groundwater withdrawals in 2019 and 2020, which aligns with reductions in the total water intensity in Figure 3. Without more detailed information on withdrawals, it is difficult to assert that this change in groundwater use is truly causal, but in combination with the rest of the analyses it does strengthen the conclusion that farmers substitute to groundwater to offset the decline in CAP water.

5.5. Robustness checks

A major challenge for this analysis is disentangling the effects of the bundle of policies of interest from other environmental and institutional shocks. To successfully do this, I need control observations that are not exposed to

Figure 4: Heterogeneity in Cropping by Groundwater Costs

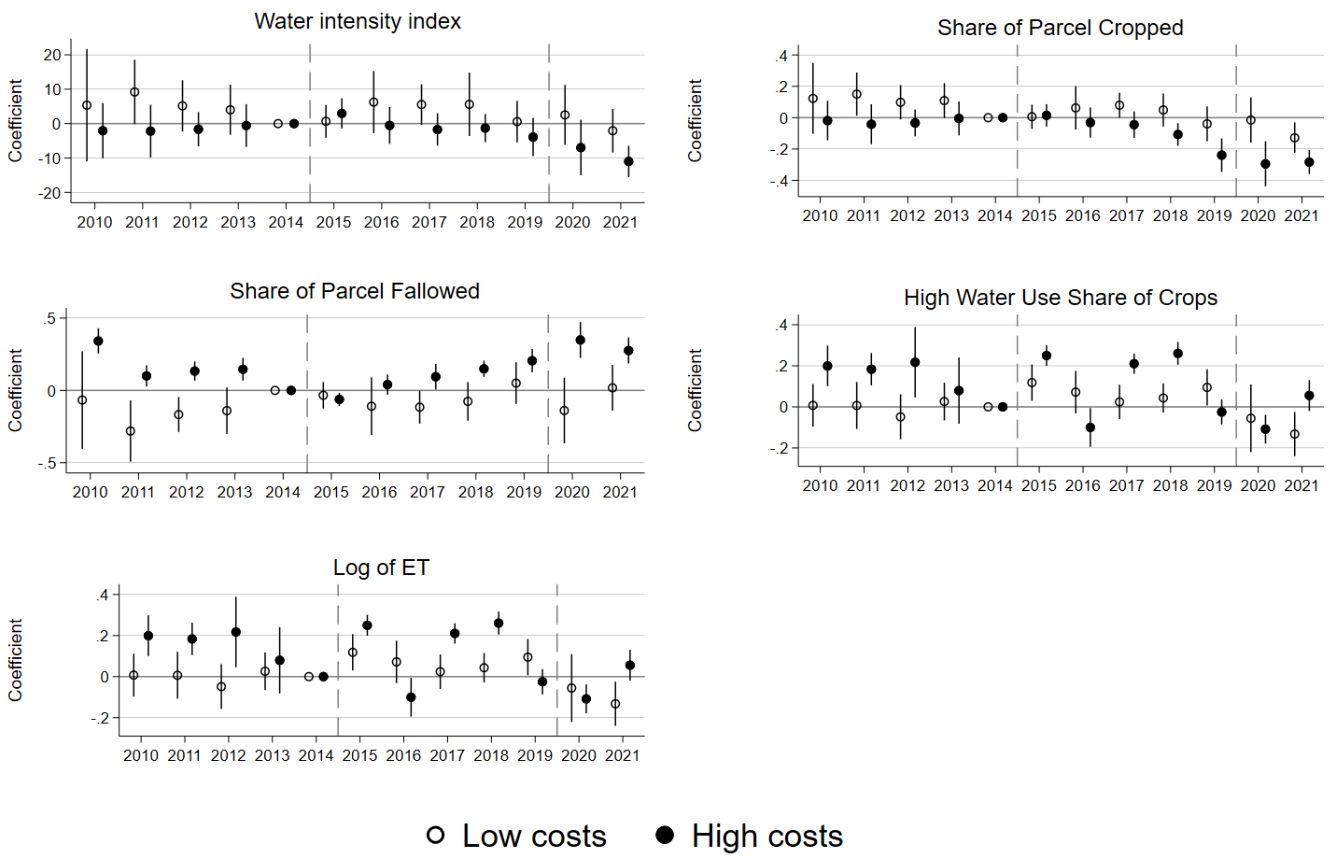

Figure plots the coefficients from the interaction of an indicator for CAP service and the year of the observation for subsamples by estimated groundwater cost. Vertical lines denote the start of the policies. The omitted interaction is for the year 2014. All specifications include climate controls and year and parcel fixed effects, and the ET analysis controls for the water intensity index. Control observations are weighted by the number of treated units they match to. Standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

Figure 5: Water Withdrawals

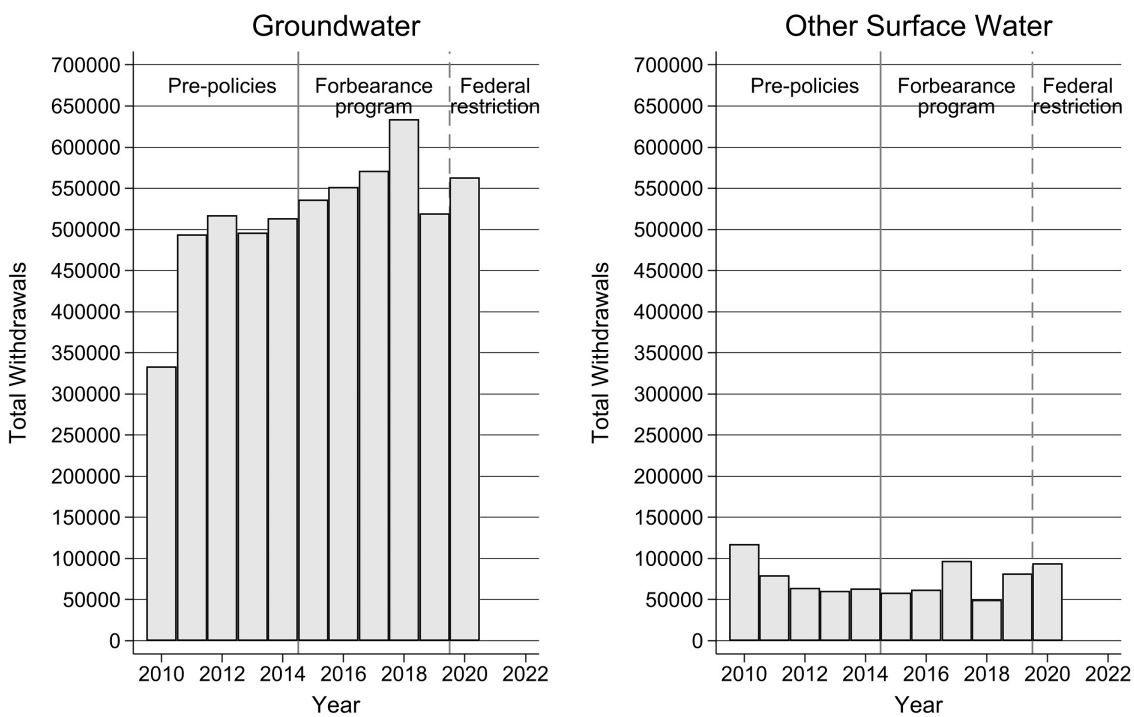

Figure separately plots the total amount of groundwater and non-Colorado River surface water withdrawals for agricultural users in the treated irrigation districts. Withdrawals are measured in acre feet of water. The vertical lines denote the beginning of the Forbearance Program in 2015 and Federal Restriction in 2020. Data on withdrawals over time in AMAs is publicly available for the Arizona Department of Water Resources. https://new.azwater.gov/ama/ama-data other shocks the treatment group is not exposed to, but that is also exposed to potential contaminating shocks that affect the treated parcels but are not the treatment of interest. The main analysis sample uses parcels in irrigation district outside of the CAP counties as controls. Table 7 re-estimates the coefficients of interest on alternative samples which vary the selection of the control group.

Panel A of the table repeats the main results. Panel B restricts the set of potential controls used in the matching procedure to a subset of the original pool: only parcels in one of the four control counties and that were in an irrigation district which did not see more than a 20% change in delivery volume at any point. This analysis aims to limit confounding from the increase in deliveries observed for some irrigation districts in Figure A3. Panel C also runs the matching procedure on a restricted subsample of the original potential controls, selecting only from parcels in the control irrigation districts in Arizona, to eliminate confounding from state level management policies. Panels D through F redefine the set of potential controls to be untreated parcels in the three counties served by CAP. Specifically panel D defines the set of potential controls to be used for matching as the set of parcels that are in one of the three treated counties but not in a treated irrigation district. These parcels are potentially more similar environmentally, but they may be outside of an irrigation district or an AMA. Panel E narrows the set to only those that are in an AMA, while panel F is the most restrictive selecting from only parcels that are in an irrigation district inside an AMA in a CAP served county, but that do not directly receive CAP water during the sample period. These parcels are likely the most representative of the treated parcels, since they are subject to the same local groundwater management and other policies, but they are also potentially indirectly affected by CAP management.

While the magnitude and statistical significance of the estimated impact of the policy bundle on fallowing and cropping varies, the main take away is similar across almost all of the specifications: farmers on average reduced the amount of land planted. The narrower control definitions used in panels D through F show that more of this reduction is through fallowing, while panels A and C suggest more is through land retirement. The estimated impact on the amount of crops that are planted that are high water is sensitive to the selection of control parcels. Panels A through C show an increase in the amount of high water crops planted, while D through F show an economically insignificant decrease. The net effect of these differences in coefficients leads to Column 1 showing large negative effects on total water use for panels D through F, and small economically insignificant declines for panels A through C. The effect estimates for ET are also quite sensitive to sample selection. Across the alternative specifications, it appears that farmers consistently reduce the amount of land planted in response to the policy bundle. They do not rely on substitution towards lower water use crops to offset the decline in surface water supplies. The total estimated reduction in water use is consistently smaller than 35% of the pre-treatment levels (7.4 inches), meaning that there is not a one for one reduction in surface water supplies to estimated water use.

In addition to varying the selection of the control parcels, I also include several other robustness checks. First, Table A5 of the appendix repeats the main analysis on the unmatched sample and a sample selecting controls with coarsened exact matching on quintiles of the variables used to predict the propensity score in equation 4. Both of these alternative samples show a larger average decrease in water intensity (about 4 inches per acre) since they find no change in the amount of high water use crops planted. Event studies using the unmatched sample are also shown in the appendix with Figure A5. Table A4 shows the main findings are robust to using the main matched sample re-weighting observations as discussed in Section 4.1.

6. Discussion

In total the results show that in response to the policy bundle, farmers continue to plant high water use crops but plant less. The net water use response to the policies is less than the total reduction in surface water supplies. Heterogeneity in the response by estimated groundwater costs suggests that farmers mitigate some of the surface water reductions by substituting to alternative water sources such as groundwater.

6.1. Change in water use

The results from Tables 3 and 4 find that while on average farmers reduced the amount of cropped land, they planted more alfalfa leading to a small, statistically insignificant decrease in water intensity. The continued planting of high water use crops is a finding that is consistent with previous research on California farmers (Burlig et al., 2021; Hagerty, 2021). Other research has found a greater reliance on crop switching in different climate

Table 7: Alternative Control Groups

	(1) Water Intensity	(2) Cropped	(3) Fallowed	(4) High Water Crops	(5) Log of ET
Panel A: Main sample					
CAP × Post 2015	-0.892	-0.081**	0.041	0.048**	0.084**
	(1.446)	(0.024)	(0.027)	(0.013)	(0.033)
Obs	733,872	733,872	733,872	530,426	670,763
R-Squared	0.669	0.752	0.517	0.302	0.975
Panel B: Stable deliveries					
CAP × Post 2015	1.422	-0.059***	0.017	0.051**	0.074*
	(1.001)	(0.014)	(0.016)	(0.015)	(0.032)
Obs	733,872	733,872	733,872	511,954	639,087
Panel C: Arizona only					
CAP × Post 2015	-0.246	-0.043**	0.017	0.057**	0.118***
	(1.161)	(0.012)	(0.015)	(0.015)	(0.034)
Obs	733,848	733,848	733,848	482,331	646,450
Panel D: In CAP county					
CAP × Post 2015	-3.446**	-0.046**	0.052***	-0.008	-0.086*
	(1.317)	(0.014)	(0.014)	(0.008)	(0.028)
Obs	733,860	733,860	733,860	495,685	652,168
Panel E: In AMA					
CAP × Post 2015	-3.359	-0.041*	0.048***	-0.011	-0.087*
	(1.575)	(0.016)	(0.015)	(0.009)	(0.029)
Obs	733,776	733,776	733,776	497,911	650,310
Panel F: In AMA and ID					
CAP × Post 2015	-5.421***	-0.064***	0.068***	-0.005	-0.059
	(1.213)	(0.014)	(0.013)	(0.011)	(0.031)
Obs	732,876	732,876	732,876	564,265	698,302

Table presents the main specification for the outcomes of the estimated water intensity, share of a parcel cropped or left fallow, the share of planted land occupied by high water use crops, and log of ET. Each panel reflects a different control sample. All columns contain a parcel and year fixed effect and time varying climate controls, and column 5 controls for the water intensity index. Matched controls are weighted by the number of treated parcels in the sample that they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

contexts (Cobourn et al., 2021), which is likely to be related to differences in precipitation supplementing irrigation and the types of crops available.

To understand the cost of the policies for farmers, I construct a parcel level measure of dollar return per inch of water required for growing, based on the amount of each of the five main crops planted and the water needs per crop. Estimating equation 2 for this outcome (Appendix Table A8) shows that there is a $2.84 reduction in the return per inch of water required (scales to $34.08 reduction per acre foot). This value reflects a direct loss to the farmer compared to pre-2015 returns. This number is likely an underestimate of the true cost of the reductions in land planted, since it ignores the associated externalities such as health consequences from increased exposure to dust and agricultural chemicals for nearby populations (Sharratt et al., 2010; Johnston et al., 2019; Akhundjanov et al., 2023), and changes in local labor demand.

To conclude the discussion on water use, I would like to briefly delve into the possibility that the policy may have had a limited impact if it was reducing water supplies that were previously not being used for agricultural production. To think about this, it is relevant to know that excess Ag Pool water has historically been used for groundwater banking through the Arizona Water Banking Authority. This means that, hypothetically, if there was a sufficiently large amount of excess CAP Ag Pool water that was not being used directly for agricultural production, the CAP reduction could be pulled entirely from the banked supply without affecting the supplies used by farmers, leading to the small estimated effects. However, empirically it appears that this situation does not fully explain the results since while the amount of banked CAP water did decrease during the treatment period, the total amount of banked water from all sources (77,021 AF in 2014[19]) was significantly less than the reductions in CAP supplies. This means that some of the CAP reduction therefore had to come from Ag Pool water that was previously used for agricultural production.

Alternatively, the limited policy impact could be driven by reductions in water supplies that were previously being used inefficiently. As discussed in Section 2.1, delivery volumes within irrigation districts may be tied to previous delivery volumes or be a fixed volume, potentially resulting in farmer's taking more water than they would in absence of these delivery restrictions

[19]Data on water banked is from the Arizona Water Banking Authority annual reports. https://waterbank.az.gov/plans-reports/annual-reports

even though they must pay for the delivered water. If this were the case, the marginal product of the "excess" part of the delivery would be low so that loss of the "excess" water would have negligible impacts on total production. The limited policy impact therefore could be in part driven by this dynamic, with the "excess" water acting as a buffer supply before farmers have to reduce the use of their more productive water and in turn change planting decisions. Without more detailed data covering on-farm water use I am unable to tease out the extent that this story explains the main findings of the paper. Additionally, the variations of delivery restrictions within CAP and the irrigation districts likely means that this explanation may hold for some farmers but not others.

6.2. Alternative water sources

The analysis strongly suggests that the removal of the minimum delivery requirement opened the door for input substitution, with farmers relying heavily on groundwater to replace the reductions in Colorado River water. This is important from a policy stand point as it emphasizes the interconnection of groundwater and surface water and the need to manage them jointly. Since groundwater is a scarce resource itself, diverting excess surface water demand to groundwater is not a sustainable solution in the long run. Additionally, it is important to consider that increases in groundwater extraction are likely to further increase groundwater pumping costs as depth increases.

7. Conclusion

This paper examines how Arizona farmers on the Colorado River responded to a bundle of policies reducing surface water deliveries by 35%. The bundle consisted of policies removing minimum delivery restrictions, offering financial incentives for reduced demand, and capping delivery quantities. The analysis uses parcel-level data on the amount and types of crops planted, groundwater well permits, and constructed groundwater costs to examine how farmers adapted the way they used water and the water sources they used. Identification comes from the allocation of historic water rights, which exposed a subset of farmers to the policies reducing surface water access, while similar farmers in the region were unaffected.

In contrast with the large decline in surface water deliveries, the analysis in this paper finds a limited impact on the water intensity of plantings. In aggregate, the estimated water intensity per acre for a parcel was unchanged by the surface water reduction, in part because while the amount of cropped land declined, farmers also planted more alfalfa, a water intensive crop. While not directly observable, the analysis strongly suggests farmers supplemented their lost surface water supplies with groundwater. This conclusion is drawn from an increase in applications for new groundwater wells, heterogeneity observed in cropping outcomes by estimated groundwater costs, and increases in aggregate groundwater use. There was little variation in response across the two policies, suggesting that the financial incentives were less important than waiving the minimum delivery requirement.

Understanding how farmers respond to policy induced surface water scarcity is important for future water management. Water scarcity is a growing threat and protecting water resources is non-debatable, but reducing water use can come with costs. Reductions in planting reduces immediate farmer welfare through lost revenue which may trickle into the surrounding economy (Bickel et al., 2020). Additionally, increases in fallowed land may increase exposure to airborne particulate matter and agricultural chemicals which can have negative health consequences for individuals in the surrounding area (Sharratt et al., 2010; Johnston et al., 2019). While substitution of surface water with groundwater mitigates these concerns, it increases use of an already over-exploited resource. Overdraft of groundwater aquifers can lead to deterioration of water quality, subsidence (sinking land), and even further reduce surface water flows (Bartolino and Cunningham, 2003). Because of this, groundwater substitution is not a sustainable adaptive strategy. Policy makers then need to move forward bearing in mind that restricting surface water through policies similar to those examined here are not long term solutions.

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Online Appendices

Appendix A. Data Supplement

Appendix A.1. Data construction details

The main sample used for the analysis compiles data from several sources to create a balanced panel of parcel-level observations. I started by collected parcel boundary shape files from the individual county assessors offices for each of the seven counties. The level of detail available for each parcel varied greatly across counties, with some providing owner information and detailed land use descriptions (e.g. identifying a parcel as a vineyard versus a citrus orchard) and others providing only a unique identifier and boundary. I select only parcels in the Colorado River watershed and not on a Native American Reservation.

I first link the parcels with the USDA Cropland Data Layer (CDL) for the years 2010-2021. This raster data set spatially measures annual crop coverage and land use across the US at a spatial scale of 30x30 meter pixels, with each pixel denoting the modal crop type, natural land, or developed land within it. For each parcel, I used ArcGIS's "Summarize Categorical Raster" command to count the number of pixels belonging to each land use and crop type, as well as the total number of pixels contained within the parcel boundaries. It is worth noting that satellite imaging and pixel aggregation are subject to non-classical measurement error. Specifically, since each pixel is assigned a binary value for having a certain type of crop as the modal type or not, any error is negatively correlated with the observed outcome. The probability of measurement error is a function of image quality and detail, so it is influenced by geographic features such as slope, elevation, and cloud cover (Aliz-Garcia and Millimet, 2021). Since the sample used in the analysis covers a relatively small, homogeneous area of land, it seems reasonable that the probability of measurement error is the same across parcels.

Using the pixel counts, I constructed the share of a parcel that is fallow (cropped) as the number of pixels in a parcel categorized as fallow (with any crop) divided by the total number of pixels in the parcel. I then construct crop specific shares of land planted as the number of pixels identified as that crop type divided by the total number of pixels identified as any crop in the parcel. The share of crops that are high (low) water use is constructed as the number of pixels in a parcel that are classified as alfalfa or cotton (barley, corn, or wheat) divided by the total number of pixels in the parcel that are categorized as alfalfa, cotton, barley, corn or wheat.

To measure crop water needs, I could use the state level average amount of water applied for each crop type, which is available in 2013 and 2018 from the USDA irrigation census. I avoid this measure though, since it also implicitly accounts for changes in water applied due to changing water supplies or irrigation technologies. Another data source of water needs is Cal-SIMETAW, which measures crop evapotranspiration across California to measure crop water needs. While very recent and comprehensive data, the main limitation with this measure is that water needs vary greatly due to environmental factors so that water needs in northern California are very different from those in central Arizona for the same crop. I instead use consumptive water use from Erie et al. (1981) even though it is potentially outdated, since it provides estimates of the minimum water needed for each crop, it is invariant to endogenous changes in irrigation technology, and it is specific to southern Arizona. I identify water needs for the five most common crops, which as shown in Table A1 make up around 90% of the crops in CAP counties and are a significant share of crops in non-CAP counties as well.

Since the parcel boundaries include all parcels in the county, I use observed planting trends to select a subsample of parcels that are likely to be farms. I keep parcels that are more than an acre in size, have a non-zero pixel count, and have any crops at least twice between 2010 and 2014. Then, for each parcel-year observation in the subsample before 2014 that includes information on the type of land use, I estimate the share of the parcel that is used for any type of crop or left fallow. I use the fifth percentile of this distribution to define a threshold value of 2.6%, dropping any parcels where the share of land left fallow or dedicated to crops never exceeds the threshold value between 2010-2014. The goal of this restriction is to limit the inclusion of parcels which are either subject to small measurement error or are not growing crops for market sale (e.g. personal gardens). Table A2 shows that these sample restrictions do a fairly good job of identifying cropped land (columns 5 and 9), however the amount of parcels is much larger than the number of farms. Lastly, I drop parcels where the owner is identified as Fondomonte Arizona LLC or Arizona Valley Farm LLC. These two entities are known to be extremely large commercial farms which rely almost exclusively on groundwater, and as such are identifiable as not being treated though in the treated counties.

I then link the selected parcels to environmental attributes such as elevation, soil characteristics, temperature, precipitation, groundwater management areas, and the relevant service area for electric utilities and irrigation

Table A1: County Level Crop Choice

		CAP			Non-CAP			
Crop	All	Maricopa	Pima	Pinal	La Paz	Yuma	Imperial	Riverside
Alfalfa	38.4	57.1	15.1	34.0	36.2	30.1	39.3	30.3
Barley	3.4	8.1	8.3	8.2	3.1	1.1	0.02	1.3
Cantaloupes	0.9	0.8	0	0.8	4.2	0.6	1.0	0.7
Citrus	3.0	0.02	0	0.02	0.5	6.7	3.6	6.3
Cotton	13.3	13.8	49.0	41.2	30.7	5.2	0.8	8.2
Corn	2.7	5.9	1.7	7.5	0.2	0.5	0.3	1.1
Lettuce	2.4	0.1	0	0	0.2	10.4	2.4	0.1
Other hay	7.7	1.6	1.4	0.7	0.6	1.4	19.2	3.0
Other tree crops	0.3	0	0	0	13.1	0.2	0.06	0.6
Pecans	0.2	0.1	1.6	0.8	0.01	0.05	0.01	0.01
Sugarbeets	2.0	0.05	0	0	0	0.03	5.7	0.1
Vegetables	2.1	0.02	0	0	0.4	5.2	1.2	7.8
Wheat	12.8	4.7	17.4	3.5	7.5	9.7	16.6	30.7
Selected crop share	70.6	89.6	91.5	94.4	77.5	46.1	56.2	71.6

Table presents planting choices in the relevant county. Each row contains the county specific share of land with any crop that is occupied by the specific crop, averaged over 2010-2014. The last row shows the average share of cropped land occupied by one of the five selected crops: alfalfa, barley, cotton, corn, or wheat. The 13 selected crops reflect the union of each county's five most common crops..

Table A2: Sample to Census Comparison

	Parcel Sample				Farm Census			
	Number of parcels	Median size	Number with crop-land	Acres of crop-land	Number of farms	Median size	Number with crop-land	Acres of crop-land
Maricopa	20,686	4	17,008	270,120	2,479	5	988	222,469
Pima	1,409	13	1,080	28,669	855	9	253	36,717
Pinal	8,301	13	7,720	284,889	938	25	530	302,591
La Paz	587	40	579	38,110	125	95	84	120,001
Yuma	7,366	9	7,187	203,742	562	18	469	200,128
Imperial	8,689	40	8,434	463,594	421	255	361	487,892
Riverside	17,517	6	15,739	175,830	2,949	7	2,127	227,246

Table compares the universe of agricultural parcels in 2012 with the distribution of farms and agriculture land as measured by the 2012 NASS Agricultural Census. Cropland for the parcels is defined as land that has any crop or is fallow.

districts. I also link parcels to well locations and interpolated groundwater depth measures. Lastly, I link parcels to cumulative annual evapotranspiration (ET) measured by MODIS aboard the Terra satellite, accessed via NASA's EarthData portal.[20] ET measures evaporation and plant transpiration, where transpiration is the process of plants releasing about 97% of the water they absorb through their roots back to the atmosphere. The data is available annually at a 500 meter gridded resolution. I take the average for each parcel of the overlapping grid cells for each year to get an annual, parcel-level average measure of cumulative ET.

Appendix A.2. Supplemental data sources

Colorado River basin boundary:. Shapefile of the boundary of the Colorado River watershed and service areas is from The Babbitt Center for Land and Water Policy at the Lincoln Institute of Land Policy.[21]

[20]MOD16 version 6.1 at https://search.earthdata.nasa.gov/search

[21]https://coloradoriverbasin-lincolninstitute.hub.arcgis.com/datasets/lincolninstitute::colorado-river-basin-hydrological-boundaries-with-areas-served-by-colorado-ri

Native American reservation boundaries:. Boundaries for Native American reservations are from the National Geospatial Data Asset Portfolio dataset Federal American Indian Reservations, accessed through ArcGIS's Living Atlas repository.

Irrigation districts:. Shapefiles containing the boundaries of irrigation districts are publicly accessible through the Arizona[22] and California[23] Department of Water Resources GIS databases.

Utility providers:. Shapefiles of utility provider service areas are publicly available through the California Energy Commission[24] and the Utilities Division of the Arizona Corporation Commission[25] upon request. Per-kWh costs of energy for agricultural irrigation were manually compiled from providers' websites and rates documentation.

Active Management Area boundaries:. Shapefile of the boundaries of Active Management Areas is publicly available from the Arizona Department of Water Resources.[26]

Geographic and climate data. Data on precipitation and temperature are from the National Oceanic and Atmoshperic Administration's Climate Prediction Center.[27] Soil quality is from the USDA Soil Survey Geographic Database's Soil Hydrologic Group raster contained in ArcGIS's Living Atlas data repository. Elevation is measured from the USGS Ground Surface Elevation raster, also available through ArcGIS's Living Atlas.

explore?location=35.798875%2C-111.196487%2C6.76

[22] https://gisdata2016-11-18t150447874z-azwater.opendata.arcgis.com/datasets/irrigation-district-1

[23] https://gis.data.ca.gov/datasets/45d26a15b96346f1816d8fe187f8570d_0/about

[24] https://cecgis-caenergy.opendata.arcgis.com/datasets/electric-load-serving-entities-iou-pou/explore?location=33.600778%2C-115.168189%2C7.84

[25] https://www.azcc.gov/docs/default-source/utilities-files/electric/map-of-arizona%27s-electric-companies.pdf?sfvrsn=3983c502_6

[26] https://gisdata2016-11-18t150447874z-azwater.opendata.arcgis.com/datasets/azwater::ama-and-ina-1/explore

[27] https://www.cpc.ncep.noaa.gov/

Appendix B. Supplementary Figures and Tables

Appendix B.1. Figures

Figure A1: Irrigation District CAP Deliveries

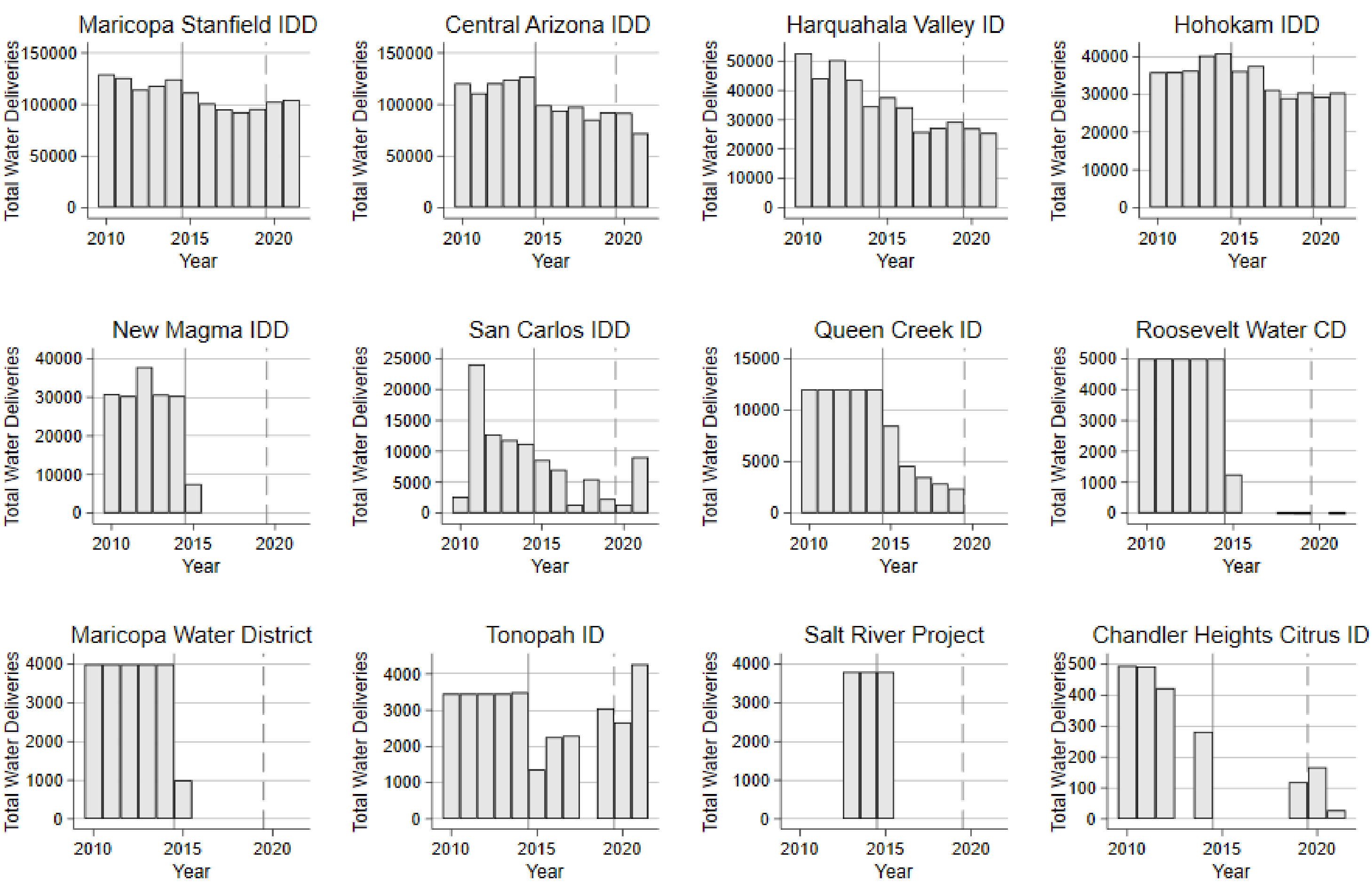

Figure plots the total amount of Ag Pool deliveries from the Colorado River to individual irrigation districts via the Central Arizona Project (CAP). Deliveries are measured in acre feet of water. The vertical lines denote the beginning of the Forbearance Program in 2015 and the Federal Restriction in 2020.

Figure A2: Drought Contingency Plan Restriction Thresholds

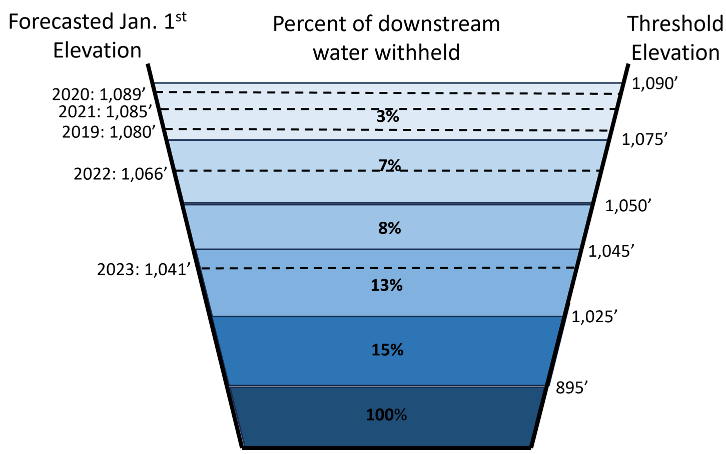

Figure graphically depicts water delivery restrictions under the Drought Contingency Plan for Lower Basin states. The threshold values based on the depth of Lake Mead are shown on the right and the corresponding reductions (as a percent of total allocations) in Colorado River water deliveries to the Lower Basin states are shown in the center. The forecasted Lake Mead elevation for January 1st of each year is shown on the left. Forecasted depths from the U.S. Bureau of Reclamation 24-Month studies (U.S. Bureau of Reclamation, 2019).

Figure A3: Control District Water Deliveries

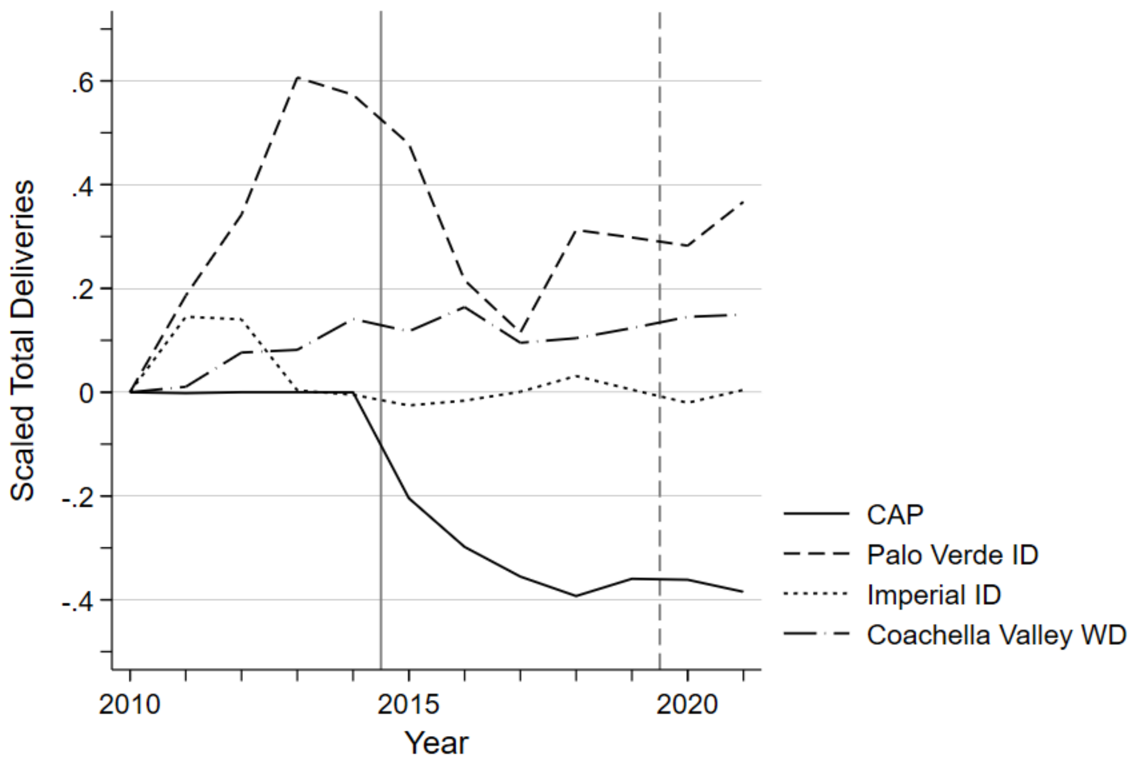

Figure plots the total amount of deliveries from the Colorado River to the largest control group irrigation districts, scaled by the district's 2010 delivery volume. The vertical lines denote the beginning of the Forbearance Program in 2015 and the Federal Restriction in 2020.

Figure A4: Leave-one-out Coefficient Estimates

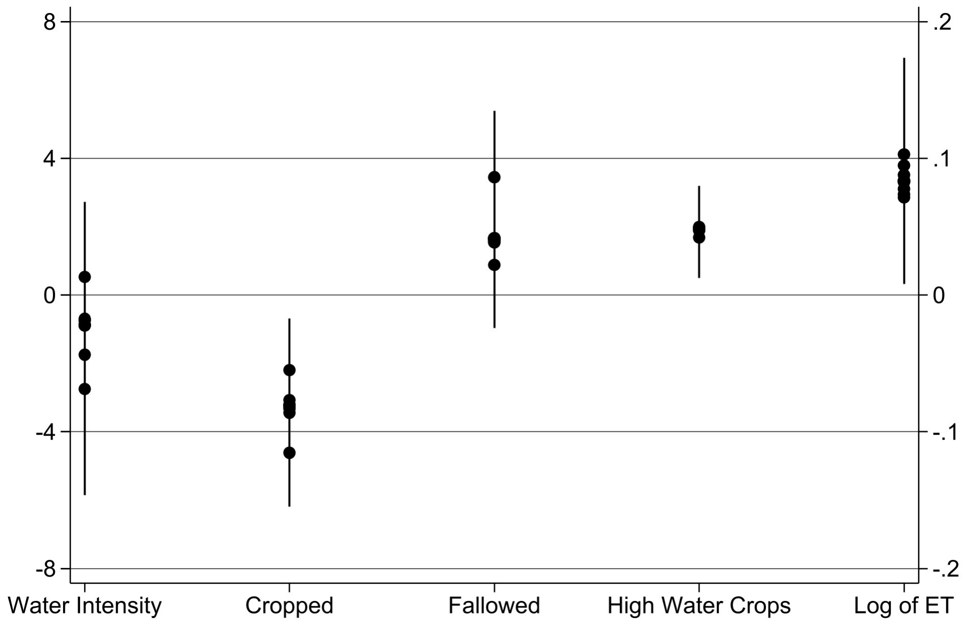

Figure plots estimates of treatment effect, β_1 from equation 2, for leave one out samples. Each sample drops one control irrigation district from the pool of matching controls, then repeats the matching procedure on the remaining parcels. The left hand y-axis is the coefficient for the outcome of water intensity index, the right hand y-axis is for all other outcome variables. All specifications contain a parcel and year fixed effect and time varying climate controls. The ET analysis includes a control for water intensity index. Matched controls are weighted by the number of treated parcels they are matched to. Bootstrapped 95% confidence intervals from the main analysis sample are denoted by vertical bars.

Figure A5: Event Study on Unmatched Panel

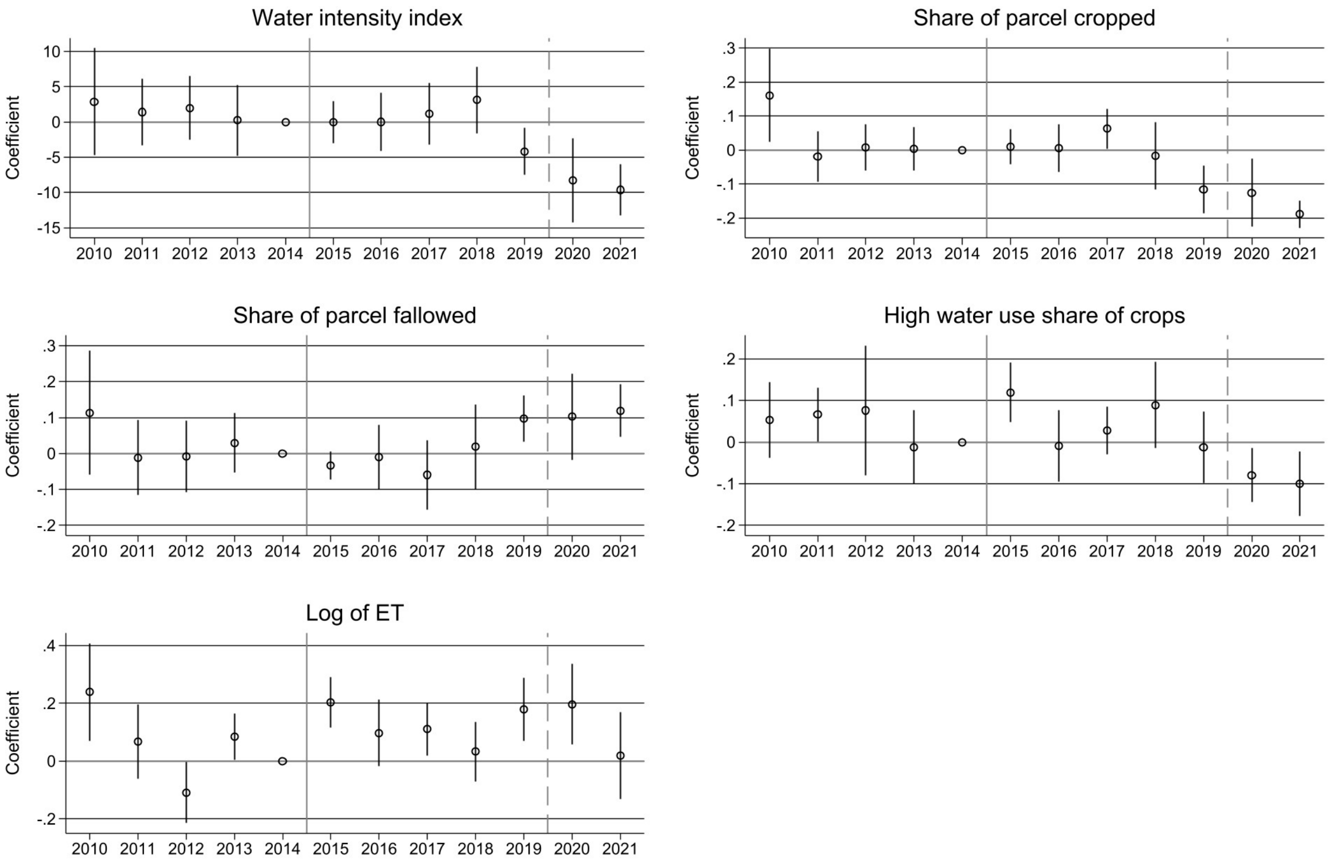

Figure plots the coefficients from the interaction of an indicator for CAP service and the year of the observation on the unmatched sample. Vertical lines denote the start of the policies. The omitted interaction is for the year 2014. All specifications includes climate controls and year and parcel fixed effects, and the ET analysis controls for the water intensity index. Wild bootstrapped standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

Figure A6: Crop Level Policy Effect Dynamics

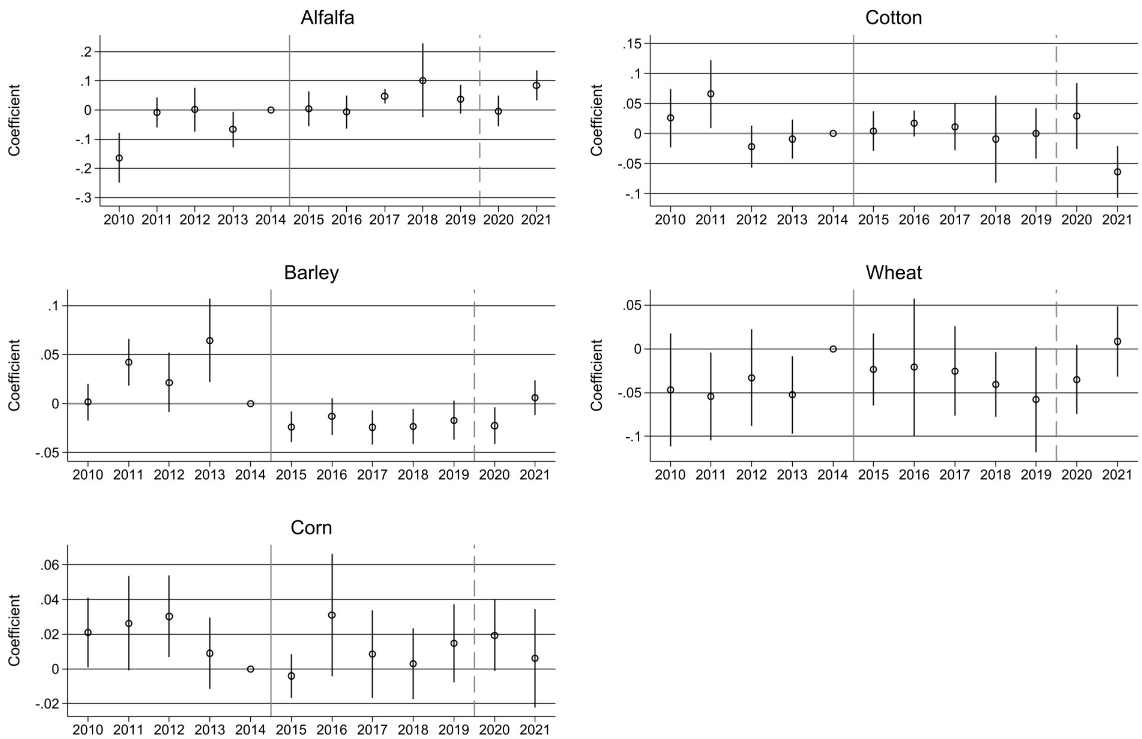

Figure plots the coefficients from the interaction of an indicator for CAP service and the year of the observation. Vertical lines denote the start of the policies, note that both policies were announced the year before implementation. The omitted interaction is for the year 2014. All specifications include climate controls and year and parcel fixed effects. Matched controls are weighted by the number of treated parcels in the subsample that they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

Figure A7: Fallowing and Cropped Land Over Time

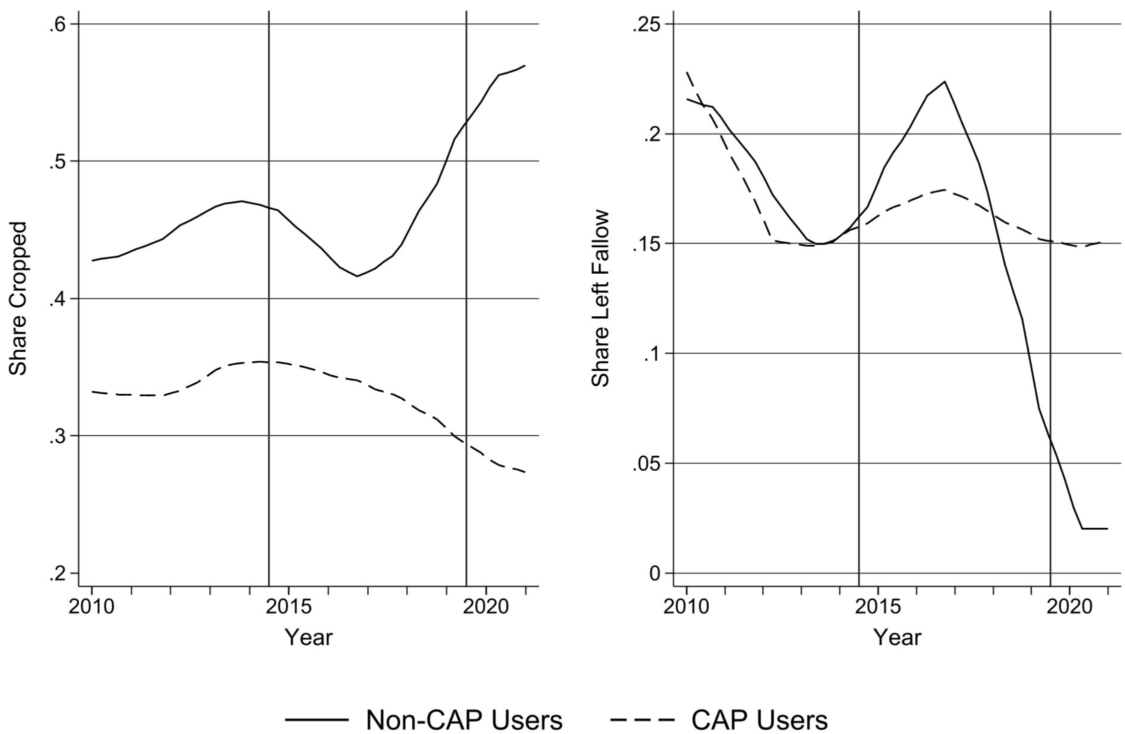

Figure depicts the kernel weighted local polynomial smoothed share of a parcel left fallow or cropped over time for CAP and non-CAP parcels. Matched controls are weighted by the number of treated parcels they are matched to.

Figure A8: Event Study on Log of Groundwater Withdrawal

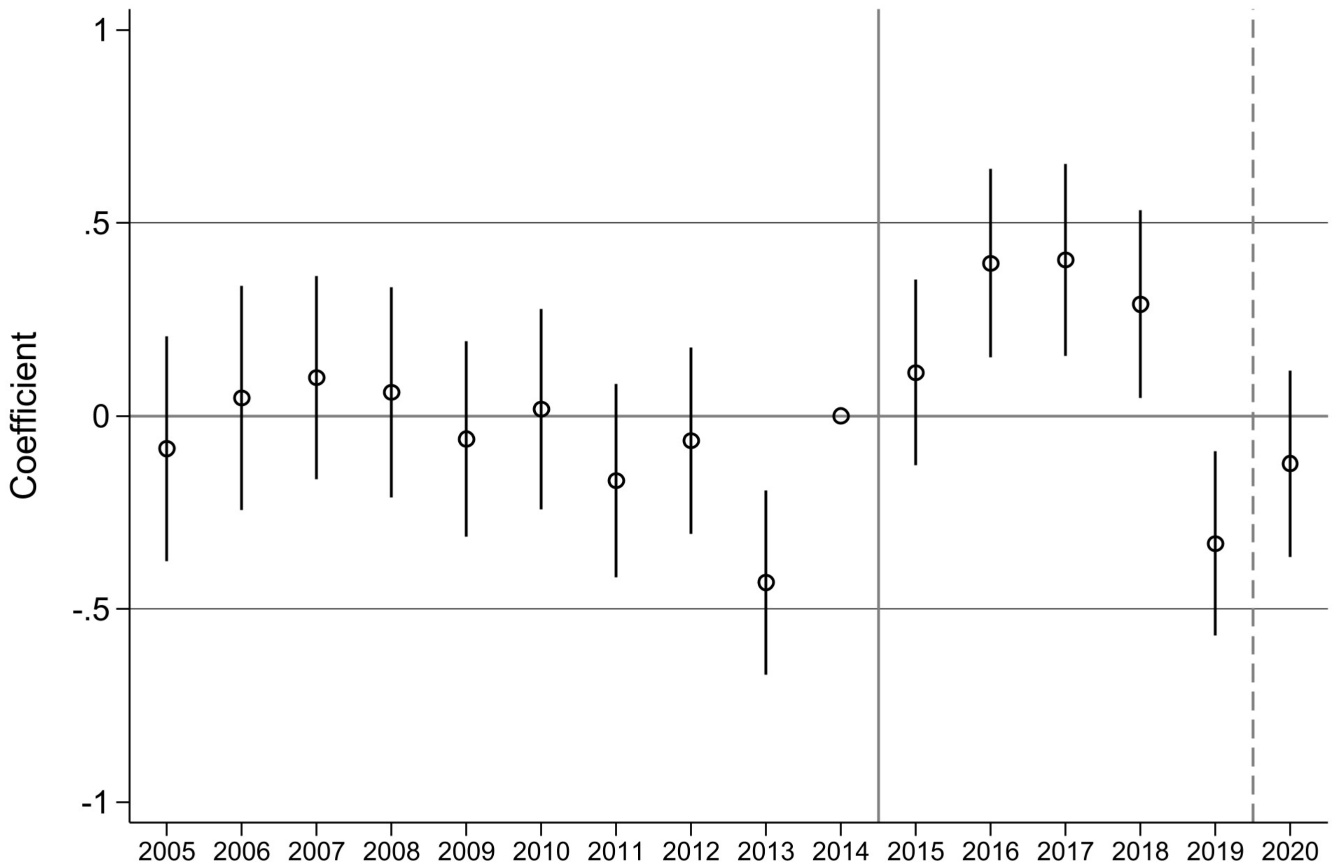

Figure plots the coefficients from a regression of the log of total water use on the interaction of an indicator for being in a treated irrigation district and the year of the observation. The observation level is at the water user-year level. Vertical lines denote the start of the policies. The omitted interaction is for the year 2014. No additional controls are included. Heteroskedastic robust 95% confidence intervals are shown by the vertical bars.

Appendix B.2. Tables

Table A3: Forbearance Program Phases

Forbearance Program	1	2	3	4	5
Years implemented	2015, 2016	2016,	2016-present	2018, 2019	2018, 2019
Forbearance amount	23%-75%	12%	0-100%	2.5%	5%
Rate discount	\$17, \$19	\$8	\$0	\$7	\$4
Number of participants	12	11	9	3	4

Table outlines differences in programs that in aggregate define the Forbearance Program. The amount of water participating districts were required to forbear is show in line 2, and the discount per acre foot on subsequent deliveries received for participation is shown in line 3.

Table A4: Alternative Weighting

	(1) Water Intensity	(2) Cropped	(3) Fallowed	(4) High Water Crops	(5) Log of ET
Panel A: Matched weight					
CAP × Post 2015	-0.892	-0.081**	0.041	0.048***	0.084**
	(1.446)	(0.024)	(0.027)	(0.013)	(0.033)
Obs	733,872	733,872	733,872	530,426	670,763
R-Squared	0.669	0.752	0.517	0.302	0.975
Panel B: Propensity score weight					
CAP × Post 2015	-2.310	-0.083***	0.025	0.009	0.079**
	(1.554)	(0.022)	(0.024)	(0.021)	(0.034)
Obs	393,408	393,408	393,408	284,481	362,394
R-Squared	0.666	0.759	0.603	0.315	0.973
Panel C: Matched weight × parcel size					
CAP × Post 2015	2.516	-0.043*	0.050**	0.057**	0.142**
	(1.254)	(0.020)	(0.018)	(0.019)	(0.033)
Obs	29,236,308	29,236,308	29,236,308	25,247,104	27,987,420
R-Squared	0.673	0.822	0.502	0.256	0.956
Panel D: Matched weight × parcel size × scalar					
CAP × Post 2015	2.305	-0.044*	0.052**	0.056**	0.148**
	(1.246)	(0.021)	(0.020)	(0.018)	(0.032)
Obs	34,714,992	34,714,992	34,714,992	30,042,583	33,392,095
R-Squared	0.664	0.804	0.483	0.256	0.954

Table estimates the main coefficients of interest from equation 2 on main sample with alternative weighting strategies. Panel A repeats the main analysis, weighting controls by the number of treated parcels they match to. Panel B weights all parcels by their propensity score. Panel C weights parcels by the matching weight from panel A times the parcel size. Panel D multiplies the weights from panel C by a scalar equal to the county level area of cropped land measured by NASS, divided by the parcel sample area of cropland in the county. All columns contain a parcel and year fixed effect and time varying climate controls. Column 5 controls for the water intensity index. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A5: Alternative Sample Selections

	(1) Water Intensity	(2) Cropped	(3) Fallowed	(4) High Water Crops	(5) Log of ET
Panel A: Propensity score					
CAP × Post 2015	-0.892	-0.081**	0.041	0.048***	0.084**
	(1.446)	(0.024)	(0.027)	(0.013)	(0.033)
Obs	733,872	733,872	733,872	530,426	670,763
R-Squared	0.669	0.752	0.517	0.302	0.975
Panel B: Unmatched					
CAP × Post 2015	-4.469***	-0.093***	0.016	-0.040	0.072**
	(0.992)	(0.021)	(0.018)	(0.031)	(0.031)
Obs	393,444	393,444	393,444	284,515	362,430
R-Squared	0.616	0.769	0.547	0.364	0.977
Panel C: Coarsened exact					
CAP × Post 2015	-4.011***	-0.034	-0.012	0.020	0.119**
	(1.711)	(0.016)	(0.013)	(0.026)	(0.041)
Obs	250,584	250,584	250,584	176,772	225,322
R-Squared	0.660	0.796	0.623	0.413	0.972

Table estimates the main coefficients of interest from equation 2 on samples selected with alternative methods. Panel A repeats the main analysis, selecting via propensity score matching. Panel B uses an unmatched sample. Panel C uses coarsened exact matching on quintiles of the variables from equation 4. All columns contain a parcel and year fixed effect and time varying climate controls. Column 5 controls for the water intensity index. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A6: County Level Crop Yields

	CAP			Non-CAP		
	Before	After	Difference	Before	After	Difference
Alfalfa	8.77	8.52	-0.25	8.33	7.84	-0.49
	(0.14)	(0.24)	(0.27)	(0.15)	(0.16)	(0.22)
Cotton	1469.11	1366.94	-102.17	1883.31	1774.25	-109.06
	(36.97)	(47.70)	(71.27)	(76.63)	(91.29)	(128.35)
Barley	119.60	121.71	2.11	131.39	129.46	-1.93
	(2.08)	(2.12)	(3.07)	(12.02)	(5.77)	(12.55)
Wheat	102.20	98.87	-3.33	96.25	97.59	1.33
	(3.61)	(1.87)	(3.69)	(9.90)	(4.85)	(9.84)

Table presents average crop yields per acre for CAP and non-CAP counties from 2010 to 2015, 2015 to 2021, and the difference between the two. Standard deviations are shown in parentheses. Corn is omitted since data is unavailable.

Table A7: Pre-2019 Difference-in-Differences Analysis

	(1)	(2)	(3)	(4)	(5)
	Water Intensity	Cropped	Fallowed	High Water Crops	Log of ET
CAP × Post 2015	0.248	-0.010	-0.054**	0.029	0.055**
	(0.693)	(0.021)	(0.018)	(0.030)	(0.024)
Obs	295,083	295,083	295,083	210,617	271,795
R-Squared	0.655	0.790	0.605	0.411	0.979

Table repeats the main analyses on the subsample of parcels observed from 2010-2018. *CAP × Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Column 5 controls for the water intensity index. Matched controls are weighted by the number of treated parcels they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A8: Dollar Return per Water Applied

	(1)	(2)	(3)	(4)
Indicator for 2015 or later	-0.219			
	(1.540)			
In CAP county	-2.158			
	(1.217)			
CAP × Post 2015	4.535*	-2.446***	-2.489**	-2.839**
	(1.785)	(0.917)	(1.009)	(1.071)
Pre-2015 treated average	18.621	18.621	18.621	18.621
Fixed effect	None	ID, Year	ID, Year	Parcel, Year
Climate controls	No	No	Yes	Yes
Obs	380,661	380,661	380,556	377,965
R-Squared	0.024	0.321	0.338	0.512

Table presents the main specification for the outcome of the estimated dollar return per inch of water required for growing, measured as the ratio of price index over water intensity index, both constructed from equation 1. *CAP × Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Wild bootstrapped standard errors are clustered at the irrigation district level and shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.