Producer Beliefs and Conservation: The Impact of Perceived Water Scarcity on Irrigation Technology Adoption

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April 19, 2022

Abstract

Agricultural producers make investment decisions based on beliefs about future returns. This article investigates how changes in beliefs about input availability affects the adoption of conservation practices. We develop a theoretical model to examine how a producer's beliefs about water shortages influence investment in more efficient irrigation technologies. We then use publicly available data on water rights and irrigated cropland to empirically identify the impact of changing beliefs about water availability on conservation decisions. We leverage a natural experiment in Colorado in which a period of severe drought and institutional change in the early 2000s led to an exogenous shock to expectations for some water right holders. We estimate that producers who experience unprecedented increases in the curtailment of their water right convert 11% more land to a more efficient irrigation technology on average. We also present evidence that adoption rates are driven more by changes in surface water availability than groundwater. This analysis provides useful insight into the role of beliefs in incentivizing adaptation to increasing water scarcity in irrigated agriculture.

Keywords: producer beliefs, conservation investment, water scarcity, drought, irrigation technology adoption

JEL Codes: Q15, Q25, D83

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Introduction

The previous four decades have been successively warmer than any decade since 1850, and there is now an overwhelming consensus in the scientific community that climate change is occurring (Powell, 2019; IPCC, 2021). Shifting temperature and precipitation patterns are expected to contribute to increased water scarcity, which poses a threat to food production (Mancosu et al., 2015). This is particularly relevant in arid regions, where water supplies are expected to be intensely affected (Lioubimtseva, 2004) and agriculture is often dependent on irrigation. For areas that use irrigation water derived from snowpack, accelerated snowmelt will change the timing and quantity of water available during the growing season, increasing the risk of costly shortages (Adam et al., 2009). It is estimated that water shortages result in more annual crop loss than all pathogens combined, totaling $30 billion in global production losses over the past decade (Gupta et al., 2020). Additionally, population growth and demands for municipal and environmental water place continued pressure on agricultural water needs. As overall water availability changes, maintaining agricultural output will depend on the adaptation of producers. Adopting water conservation strategies is one possible mechanism.

Understanding what motivates producers to conserve water resources is important for future planning, and while there exists a rich literature on potential conservation strategies (e.g., Howden et al., 2007), little emphasis has been placed on the role of beliefs that influence the implementation of these strategies. One reason for the lack of research in this area is that identifying events in the natural world that lead to a change in beliefs and a subsequent change in behavior can be difficult. Some literature suggests that personally experiencing an extreme weather event can lead people to believe that climate change is happening, thus increasing the inclination to adopt conservation strategies (Spence et al., 2011; Wang, 2017; Wang and Lin, 2018). Maddison (2007) finds that many farmers in Africa perceive climate change to be real, yet some still do not respond in their practices. While these studies provide important insights into attitudes on climate change, they rely on crosssectional survey data and cannot track behavioral changes over time. Overall, literature investigating how beliefs impact behavior using observational, non-survey data is scant. In this article we explore how changing beliefs about water availability affects conservation investment decisions for agricultural producers. A simple theoretical framework is developed to demonstrate the conditions under which a producer's beliefs would incentivize investment in irrigation efficiency. Then, a unique period of extreme drought and institutional reform in Colorado is leveraged as a natural experiment to compare empirical results to simulations from the theoretical model.

Beliefs about water availability play a critical role in decision-making for producers that are dependent on irrigation. In the United States, western states account for 81% of total irrigation withdrawals (Dieter et al., 2018), and productivity in many areas is dependent on surface water from snow runoff. In this area, rising temperatures cause more precipitation to fall as rain instead of snow, reducing snowpack depth and changing the seasonality of runoff (EPA, 2016). Several studies have examined recent hydrological changes in the western United States, documenting trends in earlier snowmelt-driven stream flows and declines in April snowpack (Mote et al., 2005; Hamlet et al., 2005; Mote, 2006; EPA, 2016). In addition to increasing temperature trends and evaporation rates, monthly projections of the Palmer Drought Severity Index (PDSI) suggest that climate change will amplify the length and severity of droughts while also hindering the recovery of macroscale water supplies (Gutzler and Robbins, 2011). One mechanism for agricultural producers to adapt to water scarcity is to adopt more water-efficient, pressurized irrigation systems like sprinkler or drip (Howden et al., 2007; Frisvold and Bai, 2016), but gravity systems are still prevalent throughout the western United States partially due to high costs of sprinkler investment and relatively low water prices. Carey and Zilberman (2002) use a stochastic dynamic model to demonstrate how uncertainty in water supplies creates an option value and deters irrigation technology adoption unless the expected present value of the investment exceeds the cost by a large margin. However, some empirical evidence has shown that farmers adopt new technologies to hedge against production risk (e.g., Koundouri et al., 2006). The present article provides insights into the disconnect between some theoretical predictions and empirical evidence surrounding investment in irrigation technology.

Presumably, producers hold beliefs about the probabilities of input shocks. When considering long-term investment in water conservation technologies, a farmer likely holds a belief of the probability of a water shortage. Ji and Cobourn (2021) provide an intuitive framework of expectation formation, proposing that beliefs about weather—or supply conditions—develop with an increased bias toward recent events. Therefore, experiencing disproportionately extreme events trigger larger belief revisions, and a subsequent series of events closer to long-run averages would be necessary to decrease the perceived likelihood of another extreme event. They corroborate their theoretical hypotheses empirically, finding that weather shocks significantly impact short-run planting decisions for farmers. Similarly, Cobourn et al. (2021) demonstrate that irrigators anticipating water shortages are more likely to fallow land and plant drought-resilient crops. Complementing these recent studies that focus on short-run responses, our attention lies on long-run responses. Our unique dataset of over 60 years of water right curtailment recordings alleviates our reliance on weather data in estimating producer expectations of water availability. We are able to pinpoint irrigators that directly experienced shortages, allowing us to identify changes in expectations and subsequent long-run improvements in water-use efficiency via irrigation technology adoption.

The present article contributes to the relevant literature in two aspects. First, we introduce a theoretical model to analyze the conditions under which an agricultural producer's belief of a possible water shortage would incentivize investing in a more water-efficient irrigation system. The model framework captures how risk is perceived for farmers operating under a priority-based water allocation institution through two belief parameters: (i.) the probability that water supply will be curtailed in a given year and (ii.) if curtailed, the intensity of the water loss. We then consider a range of model parameters to identify the set of beliefs in which the benefit of investing in more efficient irrigation infrastructure is highest. Since our framework captures the nuances of a priority-based water rights regime, insights on how investment decisions are influenced by beliefs are particularly applicable to the western United States, though similar regimes exist throughout the world.

Second, we capture changing perceptions of water shortage risk for farmers in northeast Colorado using a comprehensive panel dataset of irrigated cropland, agricultural water rights, and curtailment recordings. For many producers, increased water scarcity will change the perceived reliability of water right portfolios. In Colorado, producers with historically secure water rights are facing increases in curtailment due to institutional changes resulting from litigation and sustained drought in the early 2000s (Waskom, 2013). Our empirical context provides us with a unique opportunity to identify a change in beliefs about the reliability of a water supply, which allows us to measure how those belief changes affect decisions to adapt to increasing scarcity.

Our theoretical model shows that the net benefit of adopting more efficient irrigation technology increases in the probability of curtailment, holding all else constant. However, changes in the expected amount of water received (when curtailed) impacts net benefits non-monotonically. Treatment and control groups for a series of multi-period difference-in-difference estimations are determined by water right curtailments during the early 2000s shock relative to historical droughts. Results indicate that the treatment group, those who experienced an unprecedented increase in curtailment, adopted more water-efficient irrigation systems at significantly higher rates than the control group. Additionally, corn was the crop predominantly planted on the land with higher irrigation efficiency in years immediately following the shock, although total corn acreage was reduced. Corn is considered more sensitive to water stress than other popular crops grown in the region, such as alfalfa or wheat, further indicating that the shock incentivized a change in practices to hedge against production risks. Some producers in our study area supplement their surface water irrigation practices with groundwater, yet we find that long-run changes groundwater use did not differ substantially between treatment and control groups. This is, in part, due to the conjunctive governance of surface water and groundwater in Colorado. These empirical findings provide fresh evidence of the link between updating beliefs and conservation investment behavior.

The remainder of the article is organized as follows. First, we provide a brief overview of prior appropriation, the predominant water allocation system in the western United States, and present the theoretical framework used to analyze the impact of beliefs on irrigation technology investment. We then discuss our study area and the period of extreme drought and institutional reform that we leverage as a natural experiment, followed by a description of the data and modelling approach. In the final sections we present the estimation results, analyze their robustness, and conclude by discussing policy implications.

Theoretical Framework

To examine the role of beliefs about water availability on conservation investment, we develop a theoretical model describing a producer's decision to improve the efficiency of his irrigation infrastructure. We adopt the conceptual framing of a producer's irrigation water supply under a prior appropriation system from Li et al. (2019), with some simplification. After summarizing prior appropriation, we show a general condition characterizing the net benefit of investment in a conservation technology. We then impose assumptions on the parameters to estimate the impact of beliefs about input availability on the investment decision.

Water allocation in most of the western US is governed by a system of prior appropriation, a legal framework that rules over all water use. To divert water under prior appropriation, one must obtain a water right from a court or purchase an existing right. Water rights are usufructuary, meaning that the rightsholder does not own the water itself but the right to divert and use it. Rights are ranked in a hierarchy of priority determined by the date on which a user appropriated and diverted water for beneficial use, colloquially phrased as "first in time, first in right." Owners of agricultural water rights cannot divert more water for irrigation than what is decreed by their right, and when basin water supplies are insufficient to fulfill all decreed water rights, rightsholders with older water rights have priority over users with newer rights. In the state of Colorado, water rights are curtailed through a system of administrative "calls." When inflows are insufficient to satisfy all water rights holders, the State Engineer places a "call" on a stream which curtails the ability for junior water rights holders to divert. The administrative call communicates a priority level required to continue diverting water. In essence, when senior rights are unable to divert their decreed allotment, all junior upstream users must temporarily stop diverting to make more water available (Getches, 2009).

Consider a producer operating under a system of prior appropriation who uses water to grow crops. The producer owns a water right with a fixed priority level and a maximum amount of $\overline{w}$ units of water that may be diverted from a specified stream. Irrigation water w available to the producer to grow crops over a growing season is a random variable that takes the form

$$w = \begin{cases} \overline{w}, & S \geq V \\ \delta\overline{w}, & S < V \end{cases} \tag{1}$$

where S is a stochastic stream supply term, corresponding to the total quantity of water available for diversion by all water rights holders, and V is the total supply necessary within the stream system for the producer to divert the maximum quantity of water associated with the water right. If $S < V$, the producer's water right is called, and he receives a proportion $\delta \in [0, 1)$ of the total allotment. We further assume a relationship between irrigation water and crop yield equal to

$$y(w, \lambda, \alpha) = \begin{cases} (\lambda w)^{\alpha}, & 0 \leq \lambda w < w_m \\ y_m, & \lambda w \geq w_m \end{cases} \tag{2}$$

where $y(w, \lambda, \alpha)$ is the total quantity of output, $\lambda \in (0, 1)$ is an irrigation efficiency coefficient, y_m is maximum yield, w_m is the net irrigation requirement for maximum yield, and $\alpha \in (0, 1)$

is a shape parameter.[1]

Now consider the case where the producer has an existing low-efficiency, flood irrigation system and can invest in a high-efficiency, sprinkler system. The producer can pay an annualized cost of the upfront capital investment, c_s, that would permanently increase irrigation efficiency from λ_f to λ_s. Assume this producer's objective is to maximize expected profit by first choosing whether to invest in the new irrigation system, taking prices as given, and then applying water to his fields after w is realized. The profit function after realization is composed of the per unit price of output p, output $y(w, \lambda, \alpha)$, and some fixed cost of production k,

$$\pi = py(w, \lambda, \alpha) - k. \tag{3}$$

The producer holds beliefs regarding the probability that his water right will be called in a given year, $P(S < V) = \theta \in [0, 1]$, and the magnitude of water loss, $\delta \in [0, 1)$, should the call occur. Given beliefs about parameters θ and δ, and conditional on efficiency, the producer's expected profit, prior to the realization of w, is

$$\mathbb{E}[\pi] = p[(1-\theta)y(\overline{w}, \lambda, \alpha) + \theta y(\delta\overline{w}, \lambda, \alpha)] - k. \tag{4}$$

The decision to invest in the new irrigation system is modeled as binary, so the producer chooses between only two profit functions. For simplicity, we examine the payoff of investing for a single period case. The annualized expected net benefit of investment is

$$\mathbb{E}[\pi_s] - \mathbb{E}[\pi_f] = p\{(1-\theta)[y(\overline{w}, \lambda_s, \alpha) - y(\overline{w}, \lambda_f, \alpha)] + \theta[y(\delta\overline{w}, \lambda_s, \alpha) - y(\delta\overline{w}, \lambda_f, \alpha)]\} - c_s, \tag{5}$$

and assuming $\overline{w}$ is the amount of water necessary for maximum yield with flood irrigation,[2]

[1] Our choice of functional form attempts to exhibit the typical relationship between total seasonal irrigation and crop yield as represented on page 4 of Foster and Brozović (2018). We assume no yield when no water is applied, i.e., $y(w = 0, \lambda, \alpha) = 0$, since irrigated crop varieties in Colorado are often not drought tolerant.

[2] Water allotments under prior appropriation are determined by the historical consumptive use of the activity allowed by the water right, so this assumption is appropriate in this context.

i.e., the marginal productivity of water is zero beyond $\overline{w} = y_m^{1/a}/\lambda_f$, equation (5) is reduced to

$$\mathbb{E}[\pi_s] - \mathbb{E}[\pi_f] = p\theta[y(\delta\overline{w}, \lambda_s, \alpha) - y(\delta\overline{w}, \lambda_f, \alpha)] - c_s. \tag{6}$$

Lastly, we assume that a producer adopts the technology if the net benefit of investment is greater than zero:

$$p\theta[y(\delta\overline{w}, \lambda_s, \alpha) - y(\delta\overline{w}, \lambda_f, \alpha)] - c_s > 0 \tag{7}$$

or after rearranging,

$$\theta[y(\delta\overline{w}, \lambda_s, \alpha) - y(\delta\overline{w}, \lambda_f, \alpha)] > \frac{c_s}{p}. \tag{8}$$

The left-hand side of equation (8) is the difference in yields when water is called multiplied by the probability that water is called. It represents the expected gross benefit of technology adoption. As the difference increases, producers become more likely to adopt the technology. The right-hand side describes the ratio of cost to output price. As the cost of the investment increases, producers are less likely to invest while as price increases, the net benefit of adoption becomes higher, and producers become more likely to adopt. A key feature of this model is that the benefit of technology adoption comes only from reducing down-side risk. The adoption of a more efficient irrigation technology allows the producer to achieve a higher yield per unit of water when he does not receive the entirety of his water right. The highest priority farmer, $\theta = 0$, will always have an expected gross benefit equal to zero.

Parameter Simulations

We now examine the beliefs about θ and δ that incentivize adoption of the efficient technology by parameterizing the left-hand side of (8). We are only concerned with identifying where a producer would have the highest likelihood of adopting, so we focus on the range of beliefs in which the gross benefits of adoption are highest. When the gross benefits of adoption are highest, we would expect adoption to be more likely.

First, we assume the following parameter values: $\lambda_f = 0.5$, $\lambda_s = 0.9$, $y_m = 6$, and $\alpha = 0.5$.

Irrigation application efficiencies are used from Bauder et al. (2014) and maximum yield can be interpreted as tons of corn per acre (CSU Crop Enterprise Budgets 2017). We then calculate the left-hand size of (8) over the range of plausible values of θ and δ to generate a heat map displaying the areas in which the gross benefit of adoption is greatest given the producer's beliefs (Figure 1). Moving from a darker to lighter area on the map indicates an increase in expected yield, or the gross benefit from improving irrigation efficiency. The impact of θ is straightforward and monotonic. As a possible call becomes more certain, the benefit of improving water application efficiency increases. If the perceived probability of a call is 0, there is no incentive to invest.

The impact of the belief about δ is less straightforward. Holding θ constant, the net benefit is greatest around $\delta = 0.55$. When the producer expects to receive nearly all or nearly none of his water during a call, the benefit of improving water application efficiency approaches 0. If a producer were to experience a change in beliefs that moved him from a dark to light area on Figure 1, we would expect an increased likelihood of investing in the high-efficiency, sprinkler system. The region in which producers are most likely to adopt the new technology occurs when the probability of a call is perceived as high, and the volume of water lost during a shortage is close to 45% of the full right. In the empirical section of this paper, we investigate these theoretical predictions.

Study Area

In Colorado, The Water Right Determination and Administration Act of 1969, C.R.S. 37-92 et seq. (1969), designated seven water divisions based on drainage characteristics, each staffed with its own division engineer and water judge. Water Division 1 (WD1), the study area for this analysis, is highly dependent on surface water and contains the South Platte River basin (SPRB), Republican River basin, and Laramie River basin. The Colorado Water Plan (2015) provides extensive detail on all basins and water divisions, and here we summarize the details relevant to our analysis. The SPRB alone is home to approximately 80% of Colorado's population while also having the largest proportion of irrigated agriculture. Irrigated agriculture accounts for approximately 85% of total water diversions within the basin, with water supplies originating in mountain snowpack along the Continental Divide. Farmland in WD1 typically receives less than 8 inches of precipitation during the growing season (Schneekloth and Andales, 2017). In addition to 1.4 million acre-feet of average-annual native flow volume, the basin receives an additional 500,000 acre-feet in transmountain diversions. Overall, the basins in WD1 are over-appropriated, meaning the total allotted volume of water rights exceeds the current average supply, and many irrigation season water rights are continuously out of priority.

WD1 provides a relevant case study of many arid regions that are experiencing water scarcity concerns coupled with irrigation-dependent agriculture and fast growing populations. The 17 states wholly or partially west of the 100th meridian in the conterminous United States all utilize a strict or hybrid prior appropriation water rights regime (Leonard and Libecap, 2019) and depend on irrigation water for agricultural production. Of these 17 states, seven were among the top ten fastest growing states in percent growth from 2020 to 2021 (US Census Bureau 2021). Increased water scarcity due to climate change combined with increasing demands for urban uses place significant pressures on agricultural production in these areas. While there is certainly heterogeneity in producers across the western United States, many face similar problems to those represented in this study.

Agricultural producers in WD1 face uncertainty in water availability from two predominant sources. The first source is the variability in water supplies under a changing climate. The second source is institutional, as water administration is complex and constantly evolving. Colorado is experiencing rapid population growth, with increasing water demands for municipal, industrial, recreational, and environmental uses, and the administration of water law frequently undergoes changes from new legislation and court rulings as new problems emerge (Jones and Cech, 2009).

The Natural Experiment

In addition to designating water divisions, the 1969 Act determined that groundwater was to be regulated in conjunction with surface water under prior appropriation. The act introduced "augmentation plans" that allow for out-of-priority diversions so long as sufficient replacement water is supplied to prevent injury to senior users. Such plans are required to be approved through a decree of a district water court,[3] but the State Engineer was granted the ability to temporarily approve substitute water supply plans (SWSPs). SWSPs were essentially augmentation plans that could be renewed on an annual basis without official approval from the courts. Consequently, many junior users neglected to formally seek court adjudication and relied on the State Engineer for continued water use under SWSPs (Waskom, 2013). SWSPs were predominantly utilized by groundwater users who would collectively provide replacement water through recharge ponds or reservoirs.[4] Throughout the 1980s and 1990s, groundwater users in particular were accused of providing inadequate replacement water (Waskom, 2013), however exceptional precipitation and snowpack (McKee et al., 2000) veiled potential water shortages. Nearly two decades of abundant water supply meant there was little incentive to impose change within the system.

Then, in 1999-2000, Colorado experienced an unexpected combination of low winter snow accumulation and above average spring and summer temperatures that led to drought conditions across the state (Pielke et al., 2005). This made apparent that existing replacement efforts under SWSPs did not adequately cover shortfalls in water availability, and as a result, litigation was launched between two water users over misuse of SWSPs. The result of Empire Lodge Homeowner's Association v. Moyer, 39 P.3d 1139 (Colo. 2001) declared that the State Engineer did not have legal authority to approve SWSPs on an annual basis

[3]Colorado water courts are specialized state courts with water judges appointed by the state Supreme Court. Water judges have jurisdiction over all water use and administration within their water division. See `https://www.courts.state.co.us/Forms/PDF/JDF%20301W.pdf` for the application and detailed requirements for approval of an augmentation plan.

[4]The 1969 Act in Colorado integrated the administration of previously unregulated groundwater use with surface water use under the Prior Appropriation Doctrine.

and shifted more oversight of water replacement plans to the water courts.[5] Although this ultimately led to the permanent curtailment of many groundwater rights, it had a direct impact on surface water. First, producers faced increased dependence on uncertain surface water supplies during the summer months. Additionally, the number of formally decreed augmentation plans that require records of actual diversions increased dramatically in subsequent years (Waskom, 2013). Since the basins in WD1 are over-appropriated, net surface water diversions could not increase in practice. As more water rights recorded daily diversions, the State Engineer had a better understanding of actual surface water supplies, and the likelihood of calls along mainstream rivers increased.

After the institutional change, drought conditions persisted through 2009 with the most intense period occurring in 2002. In 2002, all of Colorado was in extreme drought conditions, and April snowpack was estimated at 52% of the previous 30-year average (Pielke et al., 2005). PDSI levels for WD1 reached -6 (Figure 2, top panel), a classification of drought categorized by widespread crop losses and severe water shortages that result in water emergencies.[6] The newly increased reliance on surface water, better records for actual diversions, and unprecedented drought conditions resulted in a permanent change to the call regime (Figure 2, bottom panel). The average number of days under call from 2002-2012 was two to four times that of 1982-2001 for districts within WD1 (Waskom, 2013, pp. 149-152). The change in oversight for out-of-priority diversions, combined with an unprecedented decrease in surface water supply, created an exogenous shock to the distribution of surface water available to relatively junior water rights.

[5] For more information on SWSPs and Empire Lodge Homeowners v. Moyer, see the "Guidance Documents" available at `https://dwr.colorado.gov/services/water-administration/water-supply-plans-and-administrative-approvals`.

[6] See `https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx`.

Data and Modeling Approach

To exploit the exogeneous change in surface water availability for some users, we compile an extensive dataset for WD1 on irrigated cropland, irrigation technology, agricultural surface water rights, call recordings, and population across seven observation years (1976, 1987, 1997, 2001, 2005, 2010, 2015). County-level population data is available through the Colorado State Demography Office, and the remainder of the data from Colorado's Division of Water Resources HydroBase software.[7] Information on individual water rights includes water source, point of diversion, water use type, maximum flow volume, appropriation date, and priority number. The priority number ranks all water rights in terms of seniority, determined by rights' appropriation and court adjudication dates. Information on irrigated cropland includes acreage, point of diversion, and crop type. Irrigation technology at the field level describes if a field irrigates using flood or sprinklers. Water rights, irrigation technology, and irrigated acres can be matched to a diversion structure, such as a ditch or canal, however we cannot identify the individual parcels owned by a specific water right holder. Therefore, we aggregate information to the diversion structure as the unit for analysis. Altogether we construct balanced panel of 411 diversion structures.

Since 1950, all administrative calls by the State Engineer have been recorded, which we use for our treatment design. Annual information on the length of curtailment for each water right allows us to define treatment and control groups by losses during the 2000s drought relative to historic droughts in the 1950s and 1970s (McKee et al., 2000). We assume that producers developed beliefs about the security of their water rights during drought years from the intensity of their curtailment during the historic droughts. The average number of curtailed days per year in drought period d, C_d, during the growing season (April-October) is calculated over the "historic" drought years (1950-1956 and 1974-1978) and the "recent" drought years (2000-2009) for all water rights sharing a diversion structure. Diversion structures that experienced a considerable increase in average curtailment C_d during the recent

[7] See `https://cdss.colorado.gov/software/hydrobase`.

drought period are placed into the treatment group at the following cutoff:

$$\text{Treatment} = \begin{cases} 1, & \Delta C_d \geq 50\% \\ 0, & \Delta C_d < 50\% \end{cases} \tag{9}$$

where $\Delta C_d = \frac{C_{recent} - C_{historic}}{C_{historic}} * 100$. Robustness of the 50% cutoff is examined in the next section.

In Table 1, we summarize the sample characteristics of treatment and control groups. Statistics for 2001 are reported to provide a snapshot of the sample just before the natural experiment, and it is used as the reference year for our regression analysis. From the data presented it is apparent that larger diversion structures with slightly more junior water rights were disproportionately impacted by the shock. To ensure treatment structures are not correlated spatially, we present a map of treatment and control structures in Figure 3. The location of treatment structures provides evidence that the shock was not localized to a specific area. We find treatment structures in both urban and rural areas and along a variety of different streams.

To further investigate our treatment design, we approximate the belief parameters defined in the theoretical model and impose the values on the heat map (Figure 4). Although treatment and control groups were determined by impacts during only drought years, we estimate beliefs using three 16-year periods that include both dry and wet years. Drought shocks are random, and a producer would develop beliefs about the probability of a call conditional on a variety of weather realizations. The estimate for the probability of a call (θ) is the average number of years a water right at a given structure was called during the period, divided by the length of the period. The estimate for the proportion of water received when called (δ) is the average of $(1 - \frac{\text{days under curtailment}}{\text{growing season days}})$ for the years in which a water right was called. From Figure 4 it is evident that most treatment structures shifted from darker to lighter areas in the period containing the shock (2000-2015), indicating a movement from low to high gross benefits from adopting a more water-efficient irrigation technology. The control structures do not exhibit the same movement. Although many control structures lie in an area that predicts a high benefit of adoption, our treatment designs aims to capture a change in beliefs about water availability. The relatively stable parameter estimates for the control group indicate they did not experience the drought shock to the same degree as the treatment group.

To examine the impact of the shock on the number of irrigated acres at diversion structure i in year t with technology j, y_{it}^{j}, we estimate the following difference-in-difference models:

$$y_{it}^{j} = \sum_{t}^{\tau} \beta_t^j D_i T_t + \omega^j x_{it} + \alpha_t^j + \gamma_i^j + \varepsilon_{it} \tag{10}$$

where j denotes the technology-specific model (i.e., sprinkler or flood), $D_i = 1$ if structure i is in the treatment group and 0 otherwise, and T_t is an indicator equal to 1 if $t =$ year T and 0 otherwise. The term x_{it} is county population, and α_t and γ_i are year and diversion structure fixed effects to control for time trends and omitted variables. Lastly, ε_{it} is the error term clustered at the diversion structure. As a placebo test, $D_i T_t$ includes all panel years, excluding the reference year of 2001,[8] to investigate differences prior to and after the natural experiment. Hereinafter we will refer to years 1976, 1987, and 1997 as "pre-treatment" and years 2005, 2010, and 2015 as "post-treatment."

Empirical Results

Coefficient estimates from (10) with corresponding cluster-robust standard errors are reported in Table 2. We estimate four iterations of the model with different dependent variables: the number of irrigated acres with flood technology, the number of irrigated acres with sprinkler technology, sprinkler acres as a percentage of total irrigated acres, and total irrigated acres. We include the percentage of sprinkler acres to ensure estimates in the first

[8] We provide regression results specifying different reference years in Appendix Figures A1-A3.

two columns are not biased by the behavior of larger diversion structures in our sample. Insignificant estimates for the pre-treatment variables in the first three columns indicate that differences in the outcome variables between treatment and control groups were not statistically distinguishable from zero prior to the shock. We present coefficients for the treatment variables graphically in Figure 5, with 95% confidence intervals, to check for the existence of pre-trends visually. Dashed confidence intervals indicate overlap with zero. In years after the shock, estimates become significant and increase in magnitude, suggesting that a change in behavior persisted for over a decade. By 2015, the average treatment structure adopted sprinkler technology on 723 more acres than the average control structure. This amounts to 11.2% more land converted from flood to sprinkler irrigation on average. Applying this estimate to the entire treatment group, the shock incentivized an increase of over 52,000 sprinkler-irrigated acres in our study area as of 2015.

From the theoretical model, we determined that changing beliefs can impact adoption nonlinearly depending on the direction and magnitude of movement. Looking again at Figure 4, we would expect treated units that moved to lighter areas on the bottom right panel to have higher rates of adoption. We investigate this hypothesis informally by imposing total changes in sprinkler acreage (Figure 6) and sprinkler acreage as a percentage of total acreage (Figure 7) for each structure on the bottom right panel of Figure 4.[9] A larger point indicates a bigger increase in sprinkler technology adoption. In both figures, there appears to be a greater concentration of high adoption rates near the lighter areas, where the gross benefits of adoption are predicted to be highest.

Surprisingly, there is no statistically significant impact on total irrigated acreage. Although WD1 is experiencing an overall decline in irrigated acreage (CWCB, 2015), the rate at which land is leaving production is comparable between the treatment and control groups. This suggests that the treatment group responded to the shock to water availability through more efficient use of the input on the intensive margin. The overall decline is perhaps par-

[9]Change in sprinkler acreage as a percentage of total acre is calculated as a difference. A diversion structure with 10% sprinkler acreage in 2001 and 20% sprinkler acreage in 2015 would have a 10% change.

tially explained by the negative and significant coefficient for population, suggesting that a population increase reduces irrigated acres within a county. This finding is consistent with large cities in Colorado buying agricultural water rights to meet increasing municipal demands (Pritchett et al., 2008).

In addition to irrigation technology, agricultural producers can respond to water scarcity by planting less water-intensive crops. We estimate crop-specific models using the same specification as (10) while limiting the dependent variable to total and sprinkler irrigated acres with corn, alfalfa, and wheat. We exclude results for grass pasture as there is very little sprinkler irrigated pasture in our sample. Results from the crop-specific models are presented graphically in Figure 8, again with 95% confidence intervals, and cluster-robust standard errors are available in Table 3. Regression results indicate that corn was the predominant crop planted on the new sprinkler irrigated land. On average, corn acreage accounted for 60-65% of the increase in sprinkler acreage for all post-treatment years. This result holds in 2005 despite the significant average decrease of 149 total corn acres, which was a potential short-run response to the shock. Between the three crops, corn is generally more sensitive to drought than alfalfa or wheat (Lobell et al., 2014), making this result consistent with risk-mitigating behavior. By 2015, we find significant and positive differences for alfalfa and wheat in addition to corn for the Sprinkler Acres specification. With the exception of corn in 2005, we find no significant differences in total acres post-treatment for each crop.

We also investigate the potential impacts on irrigated acreage that is supplemented with groundwater. The average number of estimated acres supplemented with groundwater in Table 1 indicates that the treatment group utilizes more groundwater to augment their irrigation practices. Since the institutional change in the early 2000s resulted in the curtailment of many groundwater rights, it is important to scrutinize what changes in sprinkler adoption can be attributed to changes in surface water versus groundwater availability. We first control for groundwater supplemented acreage in the Sprinkler Acres and Sprinkler % models to check for loss of significance and magnitude of the treatment effects, and then estimate one additional regression with groundwater supplemented acres as the dependent variable. Estimates of groundwater supplemented acreage were omitted from the primary regressions due to endogeneity concerns and potential measurement error, particularly because attenuation bias due to measurement error is amplified in fixed-effects estimations (Johnston and DiNardo p. 404, 2009). Regression results for the groundwater models are presented in Table 4, where columns (2) and (4) correspond to the models with the added groundwater control variable and column (5) to the model with groundwater supplemented acres (GW Acres) as the dependent variable. The only qualitative change to the results from the primary regressions is the loss of significance of the Treatment*2005 variable for the Sprinkler Acres model. Otherwise, the longer-term trends and Sprinkler % results remain largely unaffected. For the GW Acres model, we find a significant decrease in groundwater supplemented acreage for the treatment group in 2005, which reflects the immediate curtailment of groundwater rights after the shock. However, estimates for Treatment*2010 and Treatment*2015 are not statistically distinguishable from zero, indicating that long-term changes in groundwater use did not differ significantly between the treatment and control groups. It is therefore likely that the significant increases in sprinkler adoption in the treatment group was a mechanism to adapt to long-run changes in surface water availability due to the shift in the call regime.

In summary, we observe a short-run response to the shock in the reduction of total corn acreage and a long-run response in the increased and consistent adoption of sprinkler technology. To examine what this implies for potential water use, we use seasonal crop-water demands for corn, alfalfa, and wheat to make a back-of-the-envelope calculation of the reduction in water required for full crop yields for treatment structures. First, we multiply the 2015 coefficient estimates in Table 2 for corn, alfalfa, and wheat by the number of treatment structures. Next, we calculate the difference in the seasonal net-irrigation requirement, accounting for precipitation and soil moisture typical to northeastern Colorado, for an acre of each crop with flood irrigation versus sprinkler irrigation.[10] The difference for each crop

[10]Net crop water requirements are calculated from data presented in Schneekloth and Andales (2017).

is then multiplied by the values from the first step. In total, we estimate a potential reduced seasonal irrigation demand of 85,000 acre-feet or 28 billion gallons of water across WD1 by 2015 attributable to the change in expectations of water availability. The average Colorado household needs about 0.5 acre-feet of water per year (Waskom and Neibauer, 2014), so the demand reduction is roughly equivalent to the yearly water demands of 170,000 households.

Robustness Checks

In Figure 5, there is some evidence of pre-trends given the direction of coefficient estimates across time, particularly for the Sprinkler % model. One might attribute these trends to the difference in the average appropriation year (Table 1) between the treatment and control water rights. Given our theoretical results, it is reasonable to assume that junior water right holders would invest more in water efficient technologies than senior water rights holders, regardless of the shock to surface water availability in the 2000s. If that is the case, then our coefficient estimates could be biased. We test this supposition by limiting our sample to similar treatment and control structures and re-estimating the Sprinkler % model. We use a propensity score matching algorithm using the minimum, median, and maximum appropriation year for the water rights associated with a structure to make the distribution of all water rights between treatment and control groups as similar as possible.[11] Results from the matching exercise are presented in Figure 9. The treatment group is smaller than the control group, so we first match every treatment structure with two similar control structures (second column) and then one-to-one (third column). The first row of Figure 9 displays a smoothed density curve for the total sample and the two matched samples, and the second row displays coefficient estimates corresponding to the sample directly above. Although the densities do not completely overlap in the two-to-one matched sample, any evidence of pre-trends in the resulting coefficient estimates is virtually eliminated, and post-shock estimates

[11] We use the MatchIt package in R to perform a greedy nearest neighbor matching algorithm. Details can be viewed at `https://cran.r-project.org/web/packages/MatchIt/MatchIt.pdf`.

remain positive and significant. The one-to-one matching results in a nearly perfect overlap between densities, but the regression suffers from a small sample and estimates are not statistically significant until 2015. This exercise provides evidence that our main results are not driven by differences in seniority among the water rights at treatment and control diversion structures.

Next, we test the robustness of the 50% curtailment increase we use to define our treatment group. Our theoretical model suggests a nonlinear impact of curtailment length on the benefits of adoption, so although the 50% choice aligned well with how treatment structures moved on the theoretical heat map, larger increases in curtailment may impact behavior differently. We examine coefficient estimates for the Sprinkler % and Total Acres models with cutoffs ranging from 50% to 150% in increments of 5%. For each incremental increase, structures that no longer meet the treatment criteria are dropped from the analysis rather than moving into the control group. Results are presented in Figure 10 and Figure 11, where each row refers to the dependent variable in the model runs and each column to the treatment-year interaction term. For the Sprinkler % model, pre-treatment coefficient estimates are consistently insignificant, and post-treatment coefficient estimates are consistently significant. Nearly all coefficient estimates for the Total Acres model are insignificant. However, the magnitude of the coefficient estimates are not as stable. For the post-treatment coefficients in the Sprinkler % model, differences in average adoption rates fluctuate upwards of 5% as of 2010 and 2015.

Conclusion and Policy Implications

In this article, we explore the impact of beliefs about input availability on conservation investment decisions. We develop a theoretical model to examine the conditions under which an agricultural producer's beliefs about water shortages would incentivize investment in a more efficient irrigation technology. A simulation of model parameters is used to demonstrate a range of beliefs that maximize the gross benefit of investing in irrigation efficiency, and we test our theoretical predictions empirically. A period of severe drought and institutional change in Colorado that led to a change in expectations about the availability of irrigation water is leveraged as a natural experiment. Results suggest that agricultural producers who experienced an unexpected shock to their irrigation water supply transitioned more land from low to high-efficiency irrigation systems in the following decade. Our analysis provides evidence that input shocks can affect long-run investment in efficiency due to a change in beliefs.

This research has limitations that must be acknowledged. Subsidy programs such as the Environmental Quality Incentives Program (EQIP) that can significantly reduce the costs of investment may affect conservation decisions. Although we can observe general rates of adoption through land use changes, we do not know producer-specific costs of a sprinkler system. We also cannot observe conservation practices beyond irrigation technology and crop choice in our data. When evaluating EQIP enrollment, Wallander et al. (2013) found that many drought-facing producers adopted tillage practices that conserve soil moisture. Lining or replacing irrigation ditches to reduce seepage is another practice identified as water saving by EQIP that we are unable to detect.

It is also important to note that water rights can be bought and sold. Some rights were likely traded during our study period, which we are unable to track. Different owners may perceive risk differently, so belief revisions attributed to a single diversion structure may not be consistent across time. Also, we can only observe the decreed uses of a particular water right as they exist today. Although we limited our analysis to water rights that have a decreed agricultural use, some have gained additional uses through previous transactions. It is possible that not all water right owners with an agricultural water right are using their water for agricultural production in a given year.

Despite some limitations, our results are generally informative and have important policy and water management implications. First, drought in arid regions is expected to worsen under a changing climate, and beliefs will play a critical role in the future adoption of conservation practices in agriculture. Neglecting the role of beliefs when assessing the effectiveness of programs designed to encourage conservation efforts could provide policy makers with misleading information. For example, if a policy maker is considering the implementation of a subsidy program to promote the adoption of water-conserving technologies, it is important to understand whether non adoption is driven by conventional cost hurdles or beliefs about necessity. If beliefs are the driving factor, accelerating belief revisions before the realization of costly shortages during severe weather disruptions could bolster a more efficient path to adoption. This may be an opportunity for agricultural extension to address and build perceptions about water scarcity in arid climates. Surveys and qualitative interviews can be administered to local farmers to gauge beliefs about climate change, drought risk, and the efficacy and necessity of adaptation strategies. If climate change risk is perceived as negligible, awareness campaigns tailored to communicating water scarcity concerns in localized areas may be effective at accelerating belief changes. If climate change is perceived as a real risk, communicating the long-term benefits of increasing water use efficiency and providing better information on the possibility of future water shortages can enable producers to minimize their down-side risk. Highlighting the conservation practices of local farming operations may also facilitate belief changes, as the behavior of neighbors has been found to be influential in adoption behavior (Case, 1992). Once climate change perceptions align with a need to improve water use efficiency, disseminating opportunities that reduce costs of implementation, such as EQIP participation, can hasten the path to adoption.

One important characteristic of our study area is that all surface water and most groundwater resources are administered similarly under prior appropriation. Their conjunctive governance effectively limits their substitutability, so agricultural producers cannot rely on increased groundwater pumping when surface water supplies are low during drought. This lack of substitutability certainly affected producers' willingness to invest in technology to use surface water more efficiently. However, conjunctive governance not the case for all areas operating under a doctrine of prior appropriation for surface water. Some states in the US use a hybrid of appropriative and riparian water rights. For example, Texas groundwater is governed by a rule of capture, meaning that landowners bear the right to capture any groundwater beneath their property. In California, some groundwater is governed by a correlative rights doctrine, which is a modified rule of capture that limits the amount a landowner can extract from a common groundwater pool, often proportional to total land ownership. Agriculture in both Texas and California relies heavily on groundwater, particularly in drought years, yet flood irrigation using surface water is still prevalent.

Stricter regulation on groundwater use in arid regions may have long term benefits for agricultural resiliency. Groundwater aquifers are realistically exhaustible, since they can take long periods of time to replenish naturally. Inhibiting the ability to excessively pump groundwater during drought may prompt an earlier adoption of water conserving technologies. Improving the use efficiency of renewable surface water supplies before exhausting limited groundwater resources can increase the longevity of agricultural production under climate change.

It is worth noting that hydrological systems are exceptionally complex, and any changes to how and when water is diverted has common property resource implications. Water is considered a public good under prior appropriation, and water rights are usufructuary. If downstream users in a basin are reliant on return flows, i.e., the water that returns to the system after human use, reducing upstream flows by improving irrigation efficiency can impact their water availability. In some cases, it may not be clear if the adoption of high efficiency application technologies improves system-level performance. An area of future research that warrants attention is evaluating how uncertainty in return flows impact the overall efficiency of a basin. Return flows are difficult to track and can vary in their amounts depending on the crop being grown, soil type, weather conditions, and when the water is applied. This added uncertainty can make a system more difficult to manage, all else equal. High efficiency irrigation technologies however increase the control that a producer has to target water to a crop, which reduces the uncertainty in the value added from a unit of water that could have otherwise been applied with a low efficiency technology. Scrutinizing these uncertainties and understanding how incentives for efficient water use are aligned across producers within a basin is crucial for agricultural sustainability.

Acknowledgments

This material is based upon work supported by the National Institute for Food and Agriculture under Award No. 2018-69011-28369 and the National Science Foundation under Grant No. 1828902.

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Tables

Table 1: Summary of Characteristics of Treatment and Control Diversion Structures, 2001

	Control		Treatment	
Variables:	Mean	Std Dev	Mean	Std Dev
Irrigated Land (Acres)				
Flood Technology	1,110.88	3,814.92	2,755.17	5,721.63
Sprinkler Technology	289.91	1,502.46	894.70	2,830.55
Total	1,400.78	5,142.39	3,649.87	8,028.84
Groundwater Supplemented[a]	372.12	1,776.11	2,064.06	4,713.05
Crop Varieties (Acres)				
Corn	433.15	1,868.73	1,628.41	3,820.95
Alfalfa	483.02	2,055.93	1,149.95	2,572.18
Grass Pasture	250.54	514.26	351.02	701.01
Wheat	107.37	450.89	192.18	572.25
Other[b]	42.23	228.76	109.44	405.71
Water Rights Data[c]				
Appropriation Year	1880	13.14	1892	24.11
Number of Rights	6.13	11.46	2.90	3.52
County Population	211,001.8	136,786.1	147,749.5	122,041.8
Number of Structures	339		72	

[a]HydroBase provides estimates of surface water irrigated acreage that is supplemented with groundwater.

[b]Other crops include sugar beets, dry beans, and assorted vegetables.

[c]Refers only to water rights with decreed agricultural uses.

Table 2: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Irrigation Practices

Variables:	(1) Flood Acres	(2) Sprinkler Acres	(3) % Sprinkler	(4) Total Acres
Treatment*1976	467.0	-251.5	-0.016	215.5^{*}
	(276.2)	(214.3)	(0.022)	(94.6)
Treatment*1987	218.3	-175.7	-0.006	42.6
	(164.8)	(131.9)	(0.013)	(70.5)
Treatment*1997	139.1	-114.1	0.012	25.0
	(78.5)	(78.8)	(0.008)	(36.8)
Treatment*2005	-401.3^{**}	254.5^{**}	0.048^{***}	-146.8
	(151.8)	(87.2)	(0.012)	(82.0)
Treatment*2010	-557.6^{**}	516.7^{**}	0.077^{***}	-40.9
	(196.5)	(163.1)	(0.020)	(76.6)
Treatment*2015	-843.4^{**}	723.3^{**}	0.112^{***}	-120.1
	(305.1)	(237.5)	(0.025)	(102.5)
County Population	-0.001	-0.0007	$-2.11 \times 10^{-7*}$	-0.002^{***}
	(0.001)	(0.001)	(1.07×10^{-7})	(0.0004)
Fixed-effects:				
Diversion Structure	✓	✓	✓	✓
Year	✓	✓	✓	✓
Observations	2,877	2,877	2,877	2,877
Adjusted R^2	0.920	0.792	0.701	0.993

Diversion Structures: 411, Time Periods: 7, Reference Year: 2001

Standard errors (in parentheses) are clustered at the diversion structure level.

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 3: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Crop-Specific Irrigation Practices

	Corn		Alfalfa		Wheat	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables:	Total Acres	Sprinkler Acres	Total Acres	Sprinkler Acres	Total Acres	Sprinkler Acres
Treatment*1976	338.2	-54.9	-244.0	-169.3	-90.4	-32.2
	(195.8)	(68.4)	(171.1)	(119.9)	(56.4)	(23.2)
Treatment*1987	115.1	-56.8	-328.4^{*}	-149.4	59.0	-23.4
	(125.7)	(55.5)	(161.8)	(97.5)	(38.2)	(15.5)
Treatment*1997	18.8	-49.3	-203.5	-107.5	32.0	-8.34
	(120.3)	(59.7)	(122.4)	(67.8)	(31.9)	(12.7)
Treatment*2005	-149.4^{*}	155.8^{**}	-134.2	21.1	-28.8	-4.65
	(68.9)	(51.2)	(119.5)	(37.1)	(33.7)	(7.29)
Treatment*2010	-23.5	340.7^{**}	-204.2	54.4	88.6	72.0
	(53.8)	(103.3)	(135.4)	(40.3)	(53.2)	(37.4)
Treatment*2015	-103.5	453.2^{**}	-144.1	144.3^{*}	46.3	74.6^{*}
	(79.9)	(145.7)	(109.3)	(56.5)	(42.7)	(35.1)
County Population	-0.001^{**}	-0.0005	-0.0009^{**}	-0.0002	-0.0001	1.5×10^{-5}
	(0.0004)	(0.0005)	(0.0003)	(0.0005)	(0.0001)	(9.58×10^{-5})
Fixed-effects:						
Diversion Structure	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Observations	2,877	2,877	2,877	2,877	2,877	2,877
Adjusted R^2	0.954	0.781	0.915	0.717	0.798	0.522

Diversion Structures: 411, Time Periods: 7, Reference Year: 2001

Standard errors (in parentheses) are clustered at the diversion structure level.

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Table 4: Difference-in-Difference Estimations, Controlling for Groundwater Use

Variables:	(1) Sprinkler Acres	(2) Sprinkler Acres	(3) Sprinkler %	(4) Sprinkler %	(5) GW Acres
Treatment*1976	-251.5	-190.9	-0.016	-0.014	47.09
	(214.3)	(193.8)	(0.022)	(0.022)	(37.78)
Treatment*1987	-175.7	-207.9	-0.006	-0.007	-24.35
	(131.9)	(146.5)	(0.013)	(0.013)	(36.94)
Treatment*1997	-114.1	-134.0	0.012	0.011	-15.09
	(78.8)	(96.2)	(0.008)	(0.009)	(19.67)
Treatment*2005	254.5**	-94.8	0.048***	0.033**	-269.00**
	(87.2)	(124.7)	(0.012)	(0.013)	(100.50)
Treatment*2010	516.7**	354.5*	0.077***	0.070***	-125.36
	(163.1)	(162.9)	(0.020)	(0.020)	(85.00)
Treatment*2015	723.3**	624.5**	0.112***	0.108***	-76.31
	(237.5)	(219.5)	(0.025)	(0.025)	(58.41)
County Population	-0.0007	-0.002	-2.11×10^{-7} *	-2.46×10^{-7}*	-.0007**
	(0.001)	(0.001)	(1.07×10^{-7})	(1.07×10^{-7})	(.0002)
GW Acres	-	-1.32***	-	-5.38×10^{-5}***	-
	-	(0.232)	-	(7.96×10^{-6})	-
Fixed-effects:					
Diversion Structure	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Observations	2,877	2,877	2,877	2,877	2,877
Adjusted R^2	0.792	0.820	0.701	0.707	0.989

Diversion Structures: 411, Time Periods: 7, Reference Year: 2001

Standard errors (in parentheses) are clustered at the diversion structure level.

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

Figures

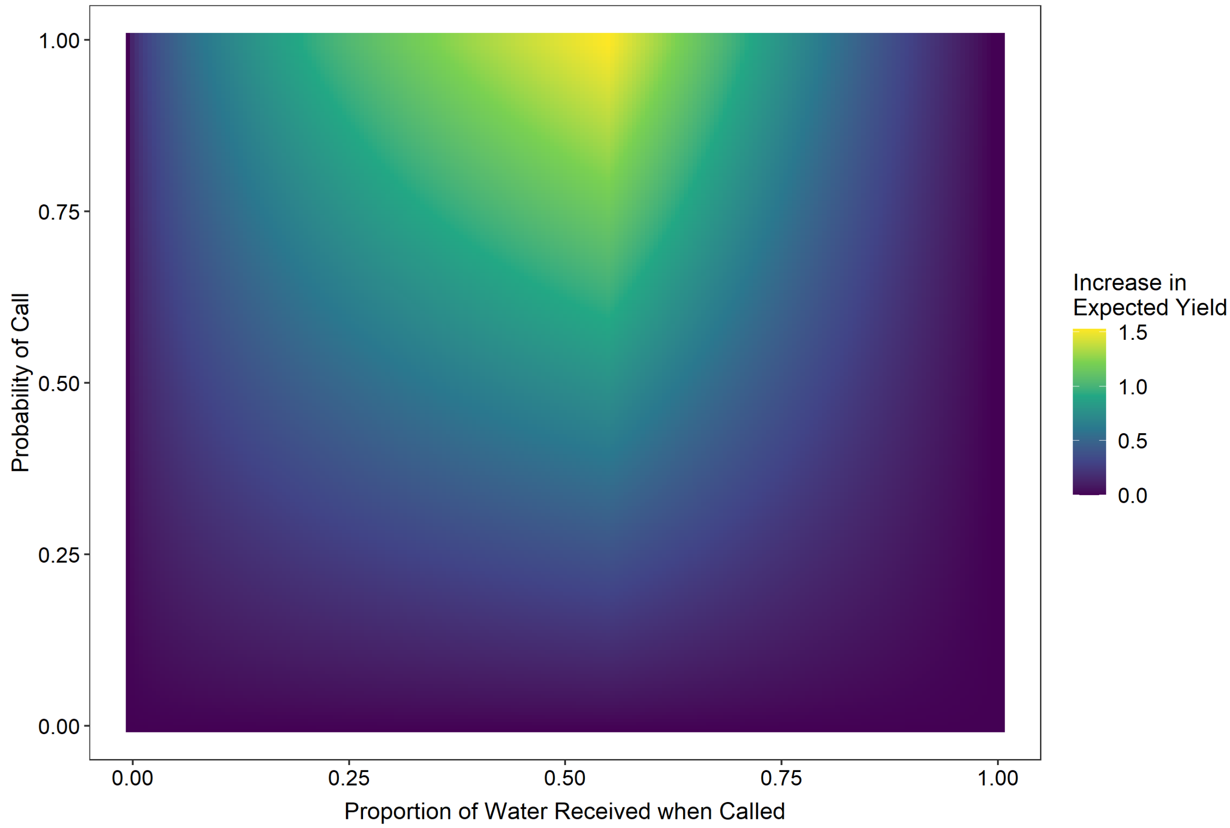

Figure 1: How Beliefs Impact the Gross Benefit of Investment

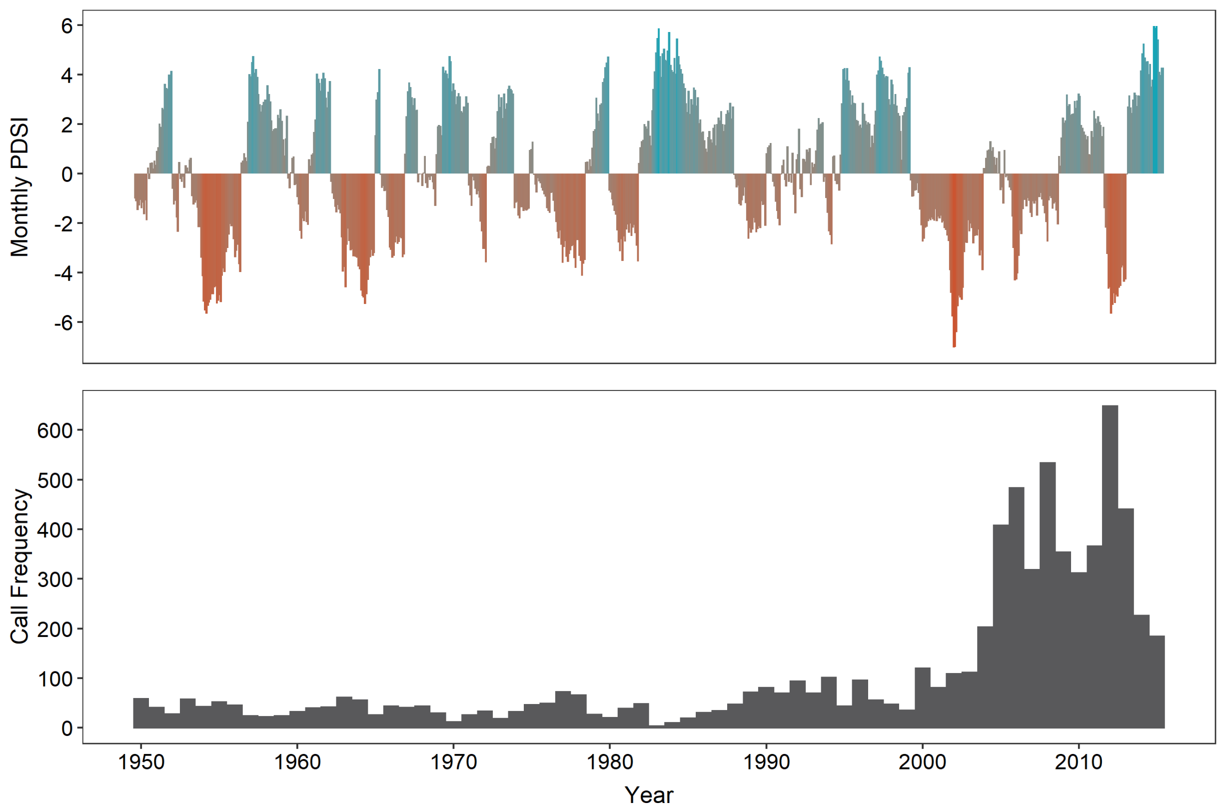

Figure 2: Monthly PDSI and Frequency of Calls by State Engineer, Colorado Water Division 1

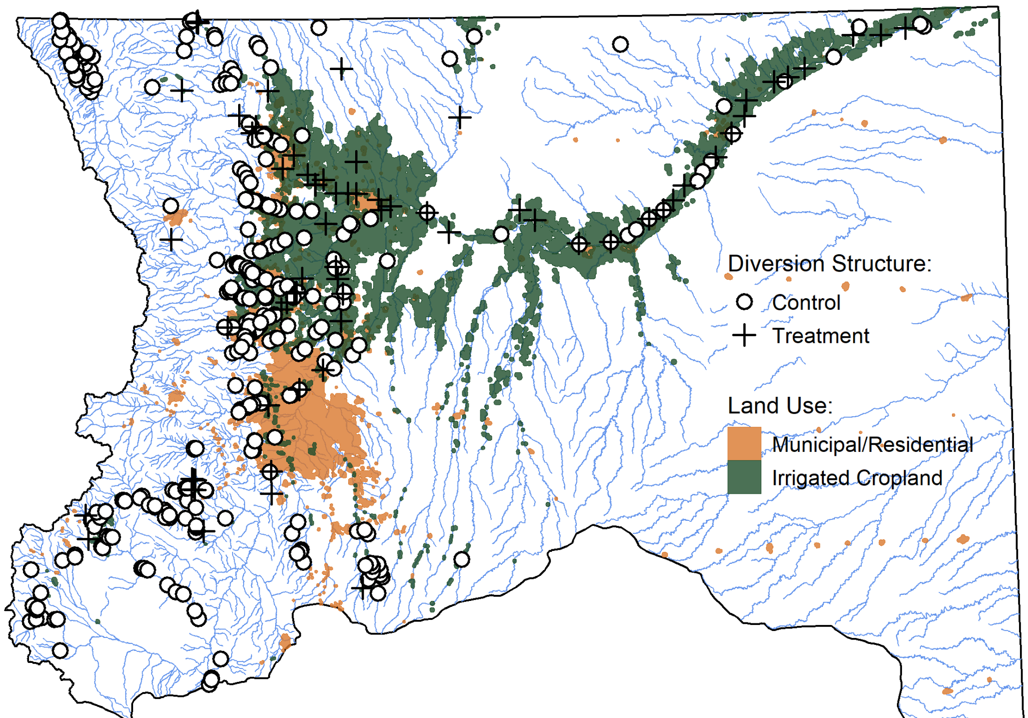

Figure 3: Treatment and Control Diversion Structure Map, Colorado Water Division 1

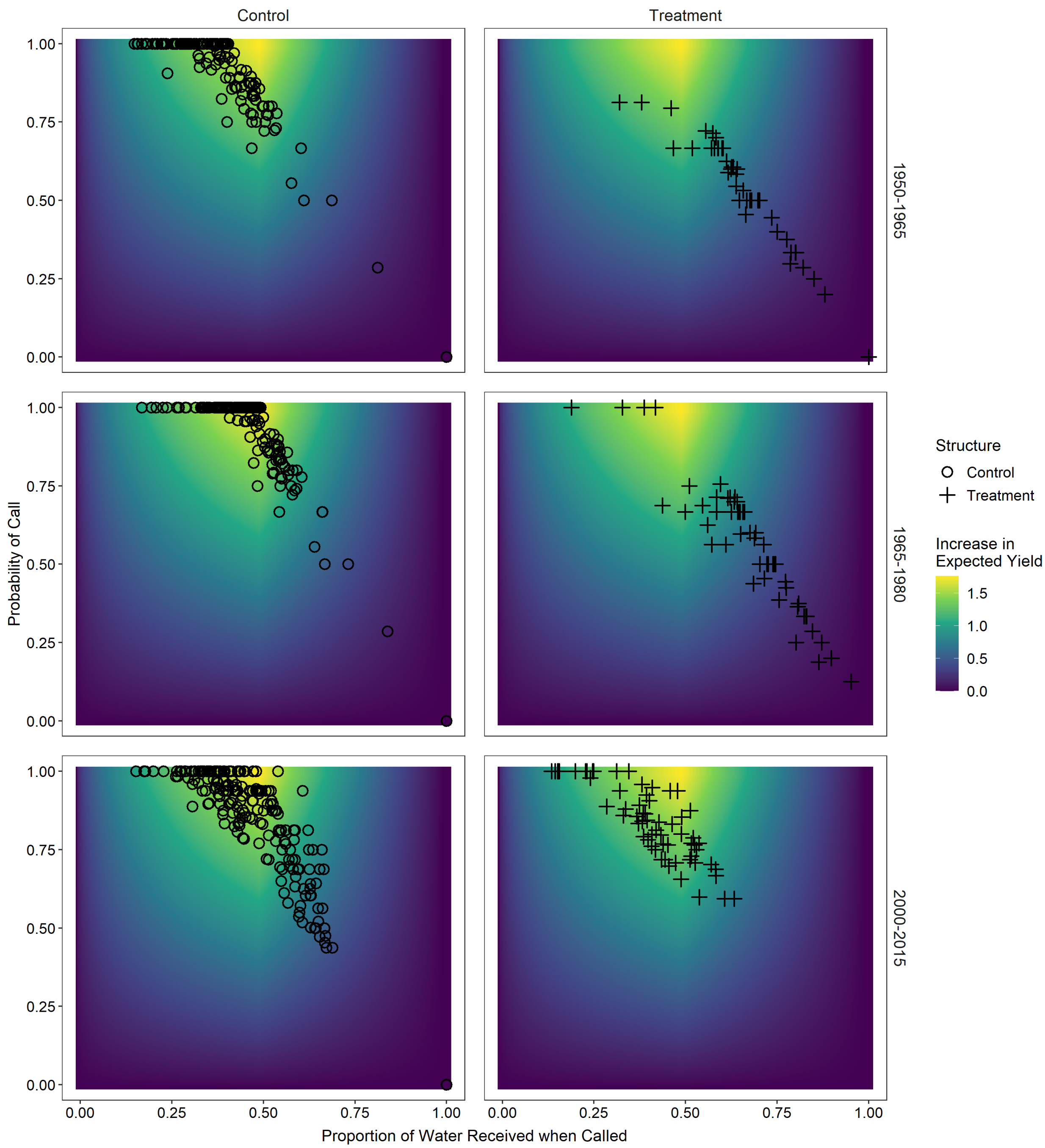

Figure 4: Estimated Belief Parameters for Control versus Treatment Diversion Structures

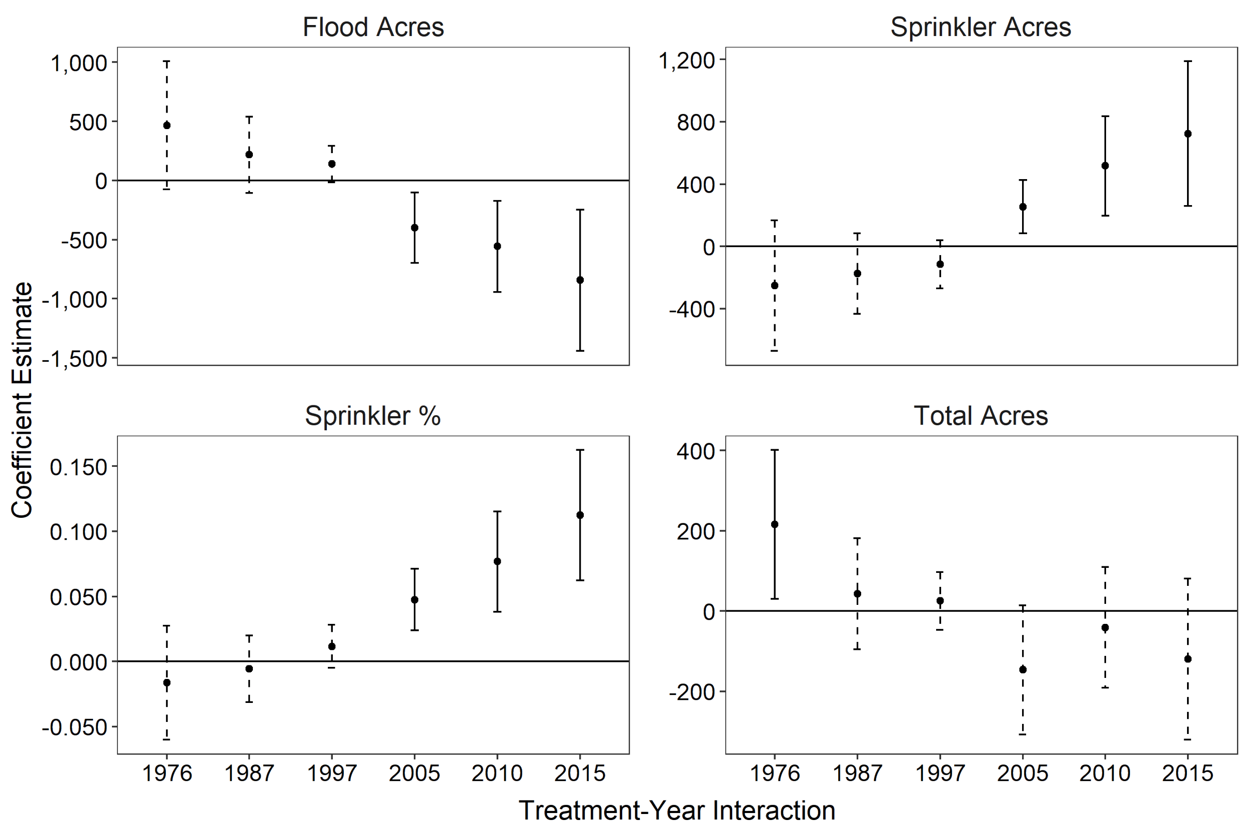

Figure 5: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Irrigation Practices

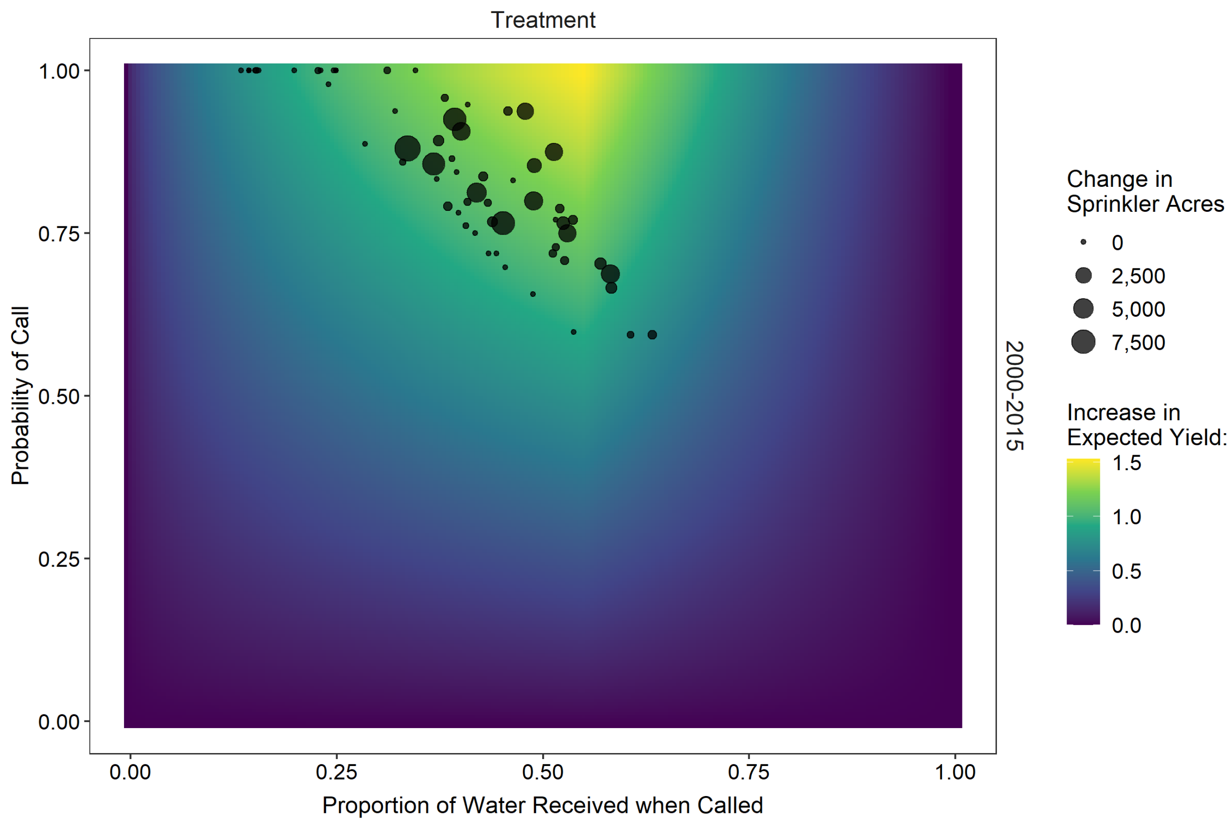

Figure 6: Nonlinear Impacts of Beliefs on the Adoption of Sprinkler Technology, Total Sprinkler Acreage

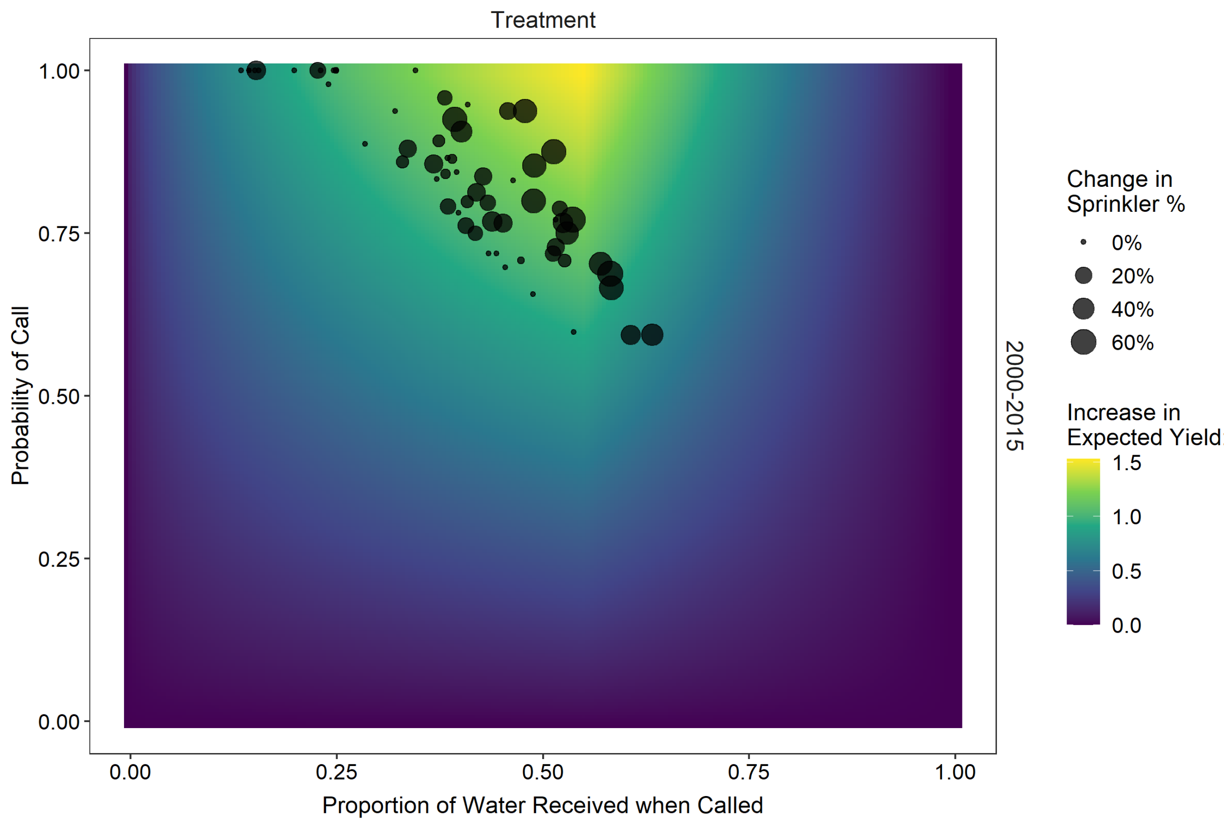

Figure 7: Nonlinear Impacts of Beliefs on the Adoption of Sprinkler Technology, Sprinkler Acreage as a Percentage of Total Acreage

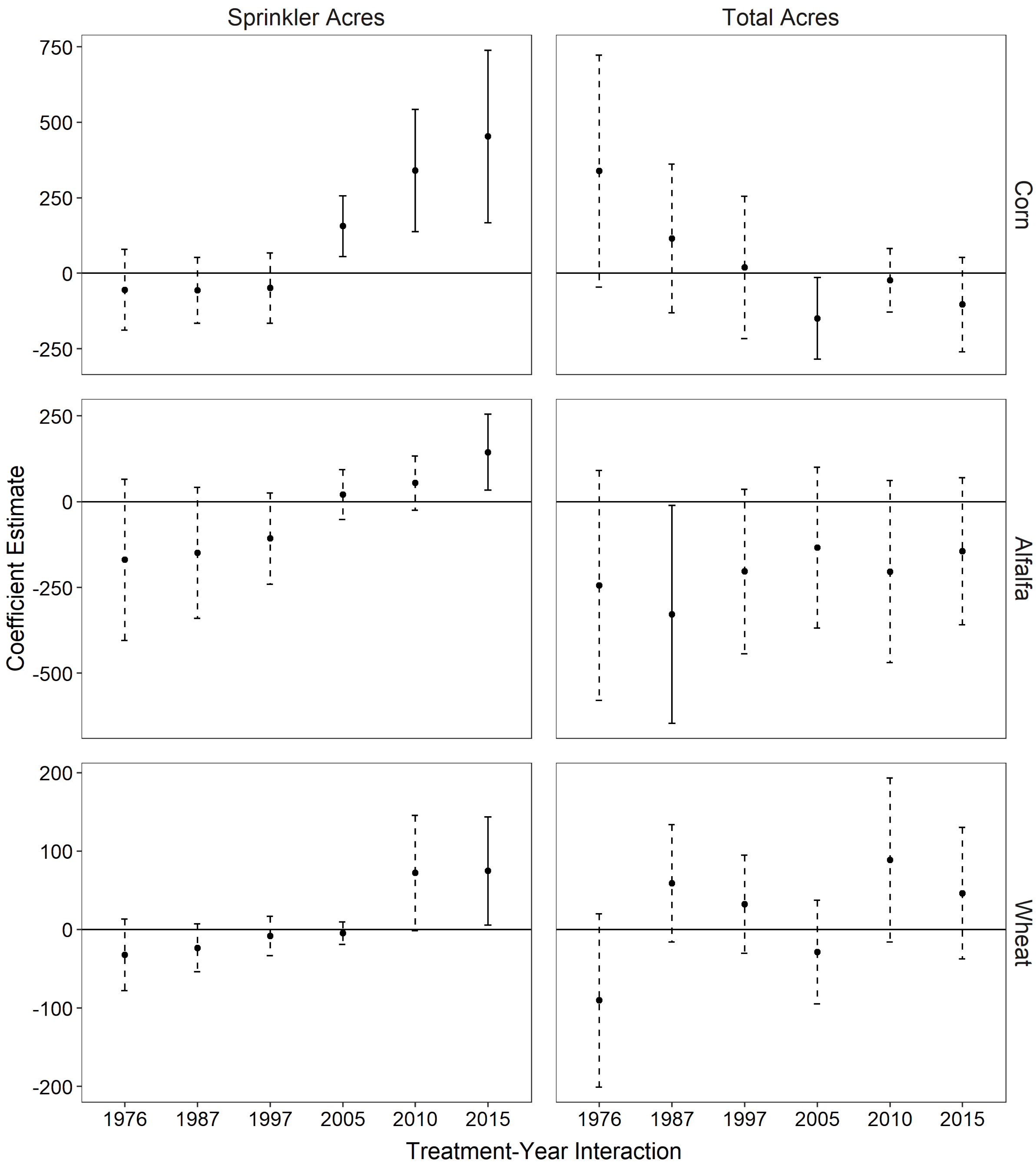

Figure 8: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Crop Choice

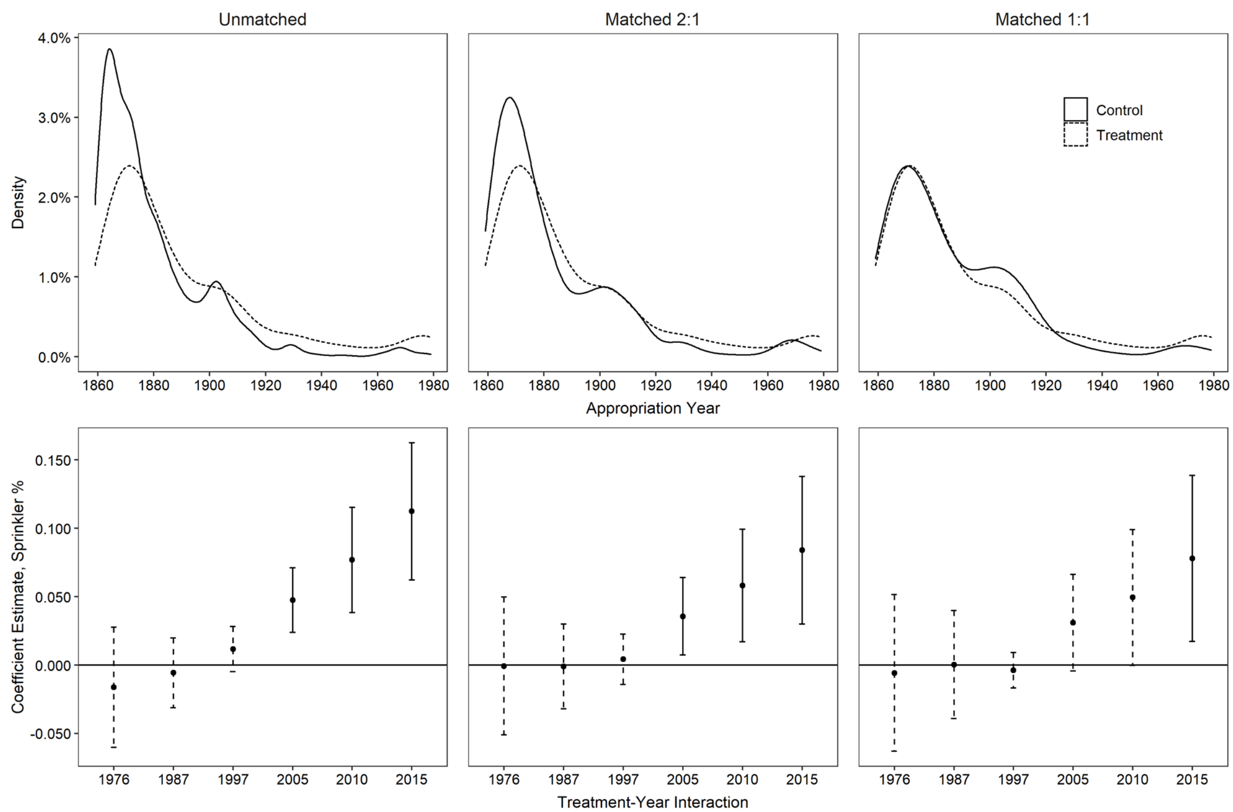

Figure 9: Difference-in-Difference Estimations Before and After Propensity Score Matching, Sprinkler %

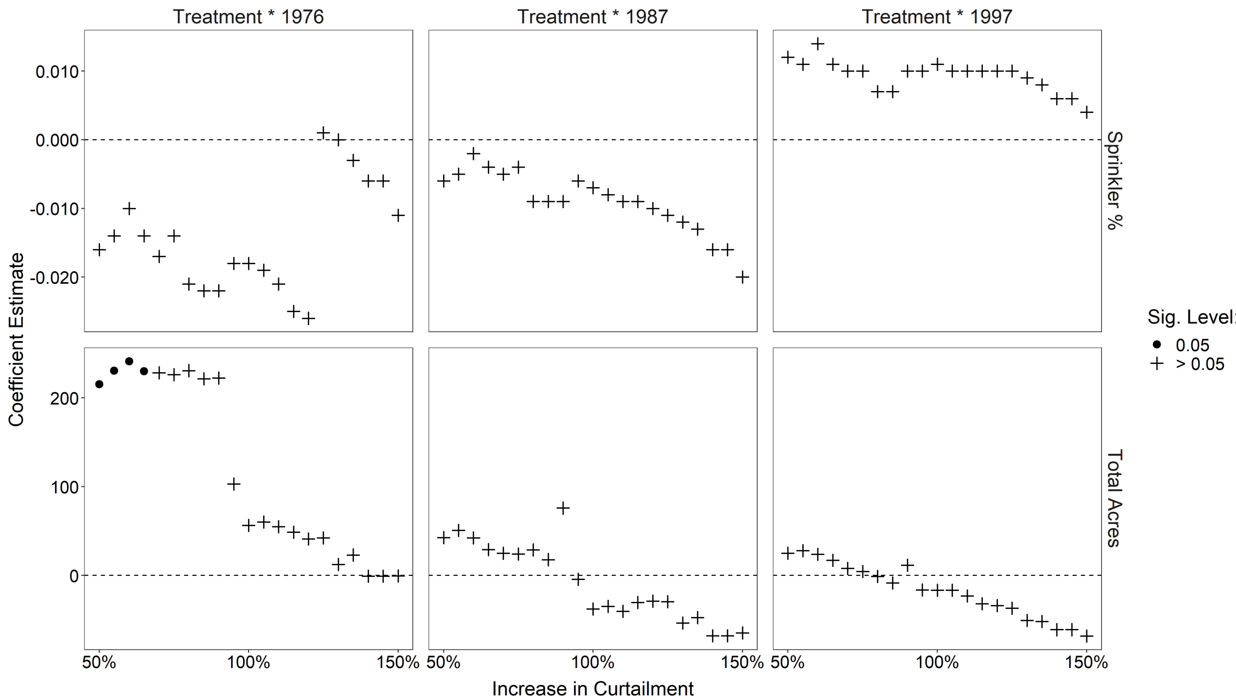

Figure 10: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Pre-Treatment

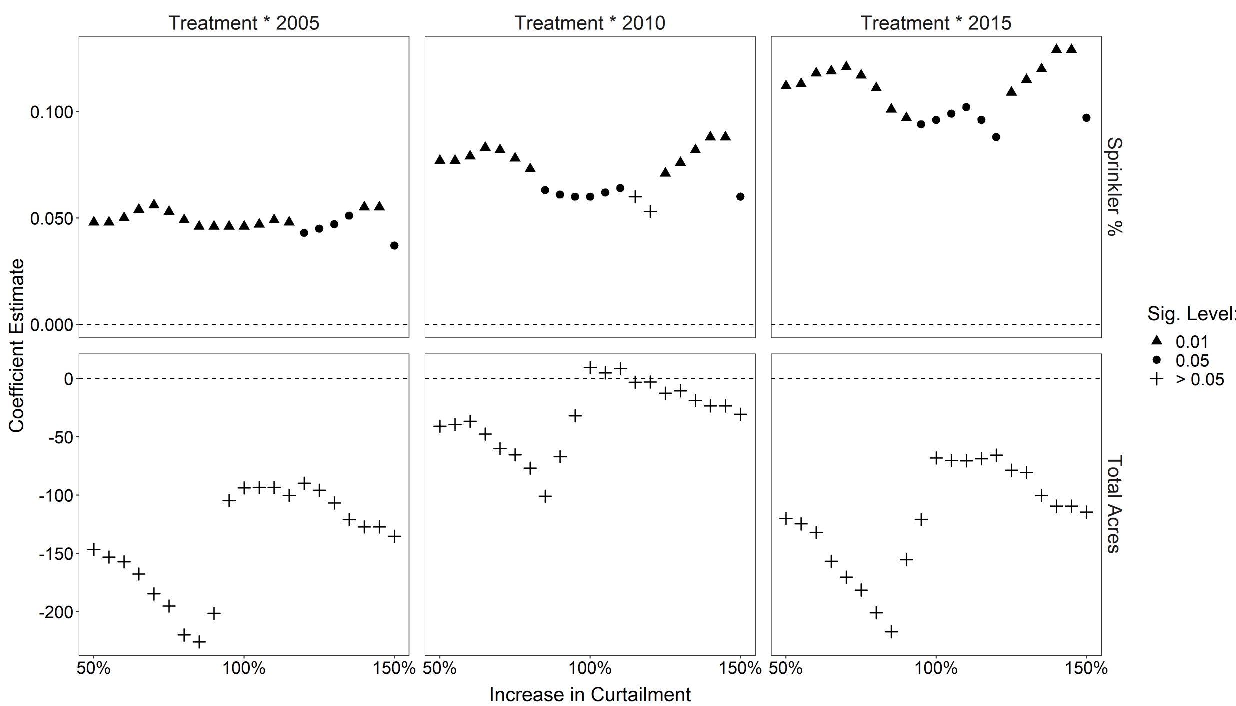

Figure 11: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Post-Treatment

Appendix

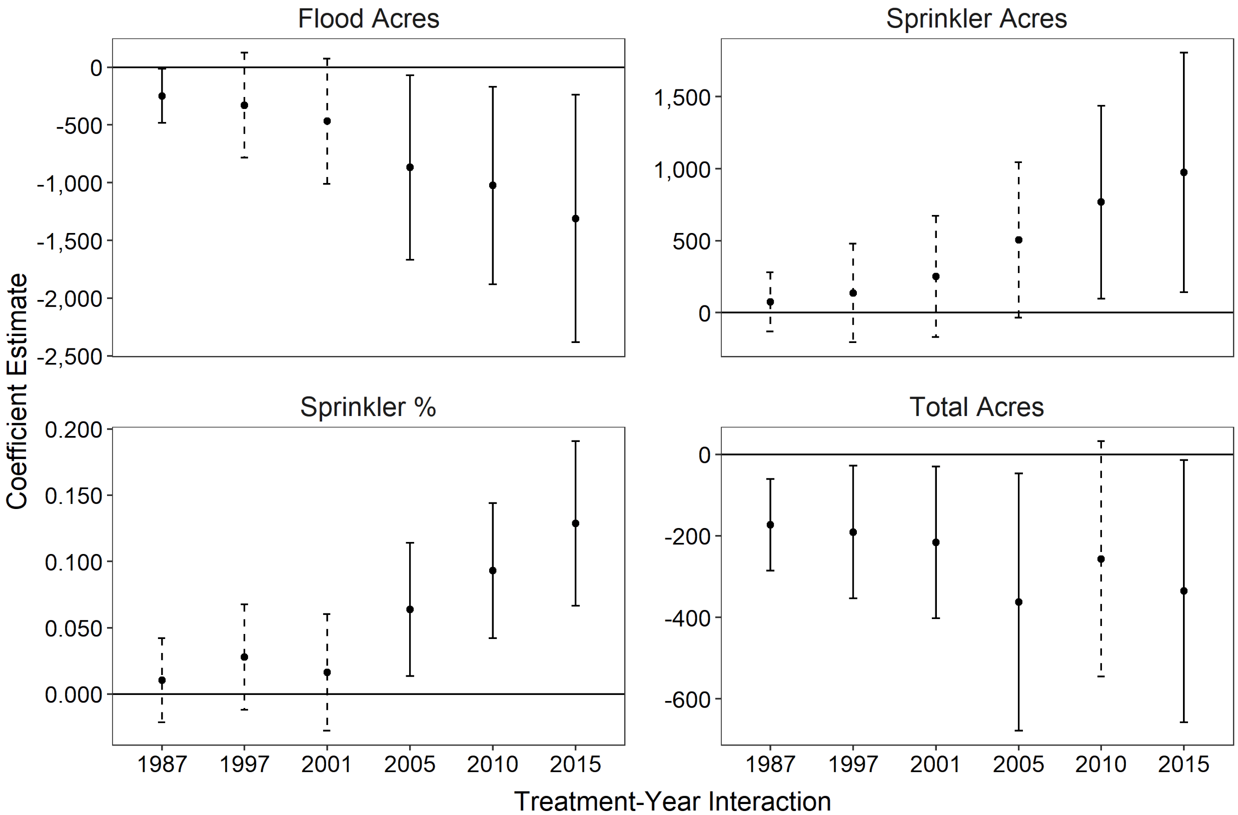

Figure A1: Difference-in-Difference Estimations, Reference Year 1976

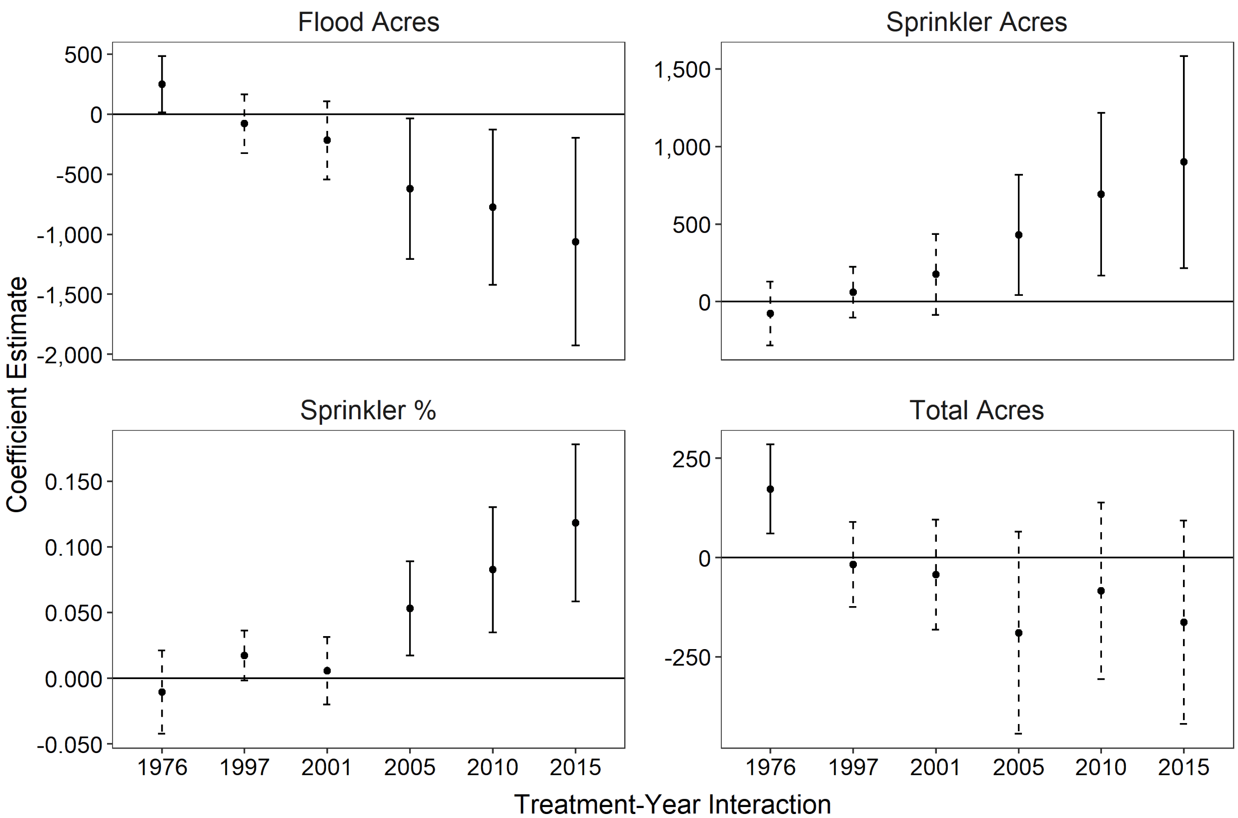

Figure A2: Difference-in-Difference Estimations, Reference Year 1987

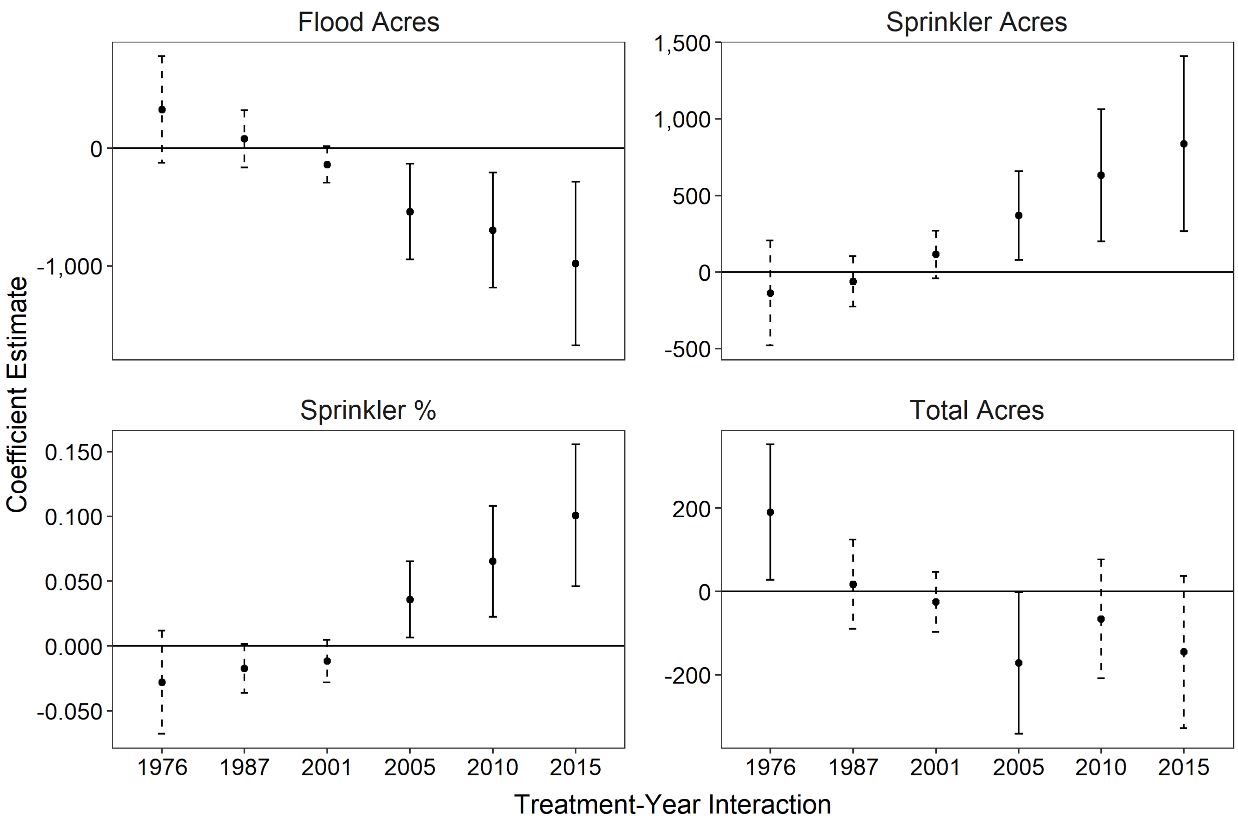

Figure A3: Difference-in-Difference Estimations, Reference Year 1997