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

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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 technology. 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. Empirical results suggest that producers who experienced an unprecedented increase in the curtailment of their water right converted 11% more land to a more efficient irrigation technology by 2015, with corn predominantly planted on the converted land. This analysis provides useful insight into the role of beliefs in incentivizing adaptation to increasing scarcity.

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

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Introduction

Scientists and policy makers agree on the need for efficient and sustainable resource planning under a changing climate (IPCC, 2021). Climate change, at the most basic level, describes a shift in the underlying distribution of weather patterns—such as temperature and precipitation—over a long period of time. As these shifts contribute to increased resource scarcity, meeting the needs of expanding populations will depend on the ability of industries and governments to adapt. Understanding what motivates people to conserve resources is an increasingly important topic, and while there exists a rich literature on adaptation strategies such as resource recovery (e.g., Guest et al., 2009) and technological investment (Lichtenberg et al., 2010), 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 identifying events in the natural world that lead to a change in beliefs and a subsequent change in behavior can be difficult.

Previous 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), but this research relies on cross-sectional survey data to analyze attitudes and cannot track behavioral changes over time. Lab experiments have also elicited beliefs from participants to measure their impact on outcomes like risk management strategies (Menapace et al., 2013) or free riding behavior (Fischbacher and Gächter, 2010), yet literature investigating how beliefs impact behavior using observational, non-survey data is scant. This article explores how changing beliefs about input availability affects conservation investment decisions in an agricultural context. 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 derived from snowpack. Shifting precipitation patterns, hotter temperatures, and 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. One mechanism for agricultural producers to adapt 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 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.

Beyond agricultural contexts, some literature shows how beliefs can affect the long-run consequences of extreme economic shocks. Theoretical models that explicitly incorporate beliefs have been introduced in the macroeconomic literature to examine the long-run impacts of deep recessions (Gourio, 2012), such as the Great Recession of 2008 (Kozlowski et al., 2020*b*) or the recent COVID-19 pandemic (Kozlowski et al., 2020*a*). The authors propose that the largest cost of an extreme shock can result from 'belief-scarring,' in which changing perceptions of the likelihood of future extreme events cause long-run investment and employment to stagnate. For agricultural producers, extreme shocks often result from

weather disruptions like drought. The net costs of extreme water shortages depend on both short-run production losses and long-run adjustments made to cope with future availability. Although the total costs of deep recessions can increase over time, the future costs of climate change can be overestimated if updating beliefs causes producers to make investments in adaptation strategies.

Presumably, producers hold beliefs about the probabilities of input shocks. For example, when considering long-term investment in water conservation technologies, a farmer 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 in-

tensity 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. Although the framework is designed to reflect producers within the context of our study area, insights gained from how investment decisions are influenced by beliefs can provide useful information for other contexts where input availability is uncertain.

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 an agricultural input, 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. 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 and research implications.

Theoretical Framework

To examine the role of beliefs about input availability, 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 surface 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 sum-

marize 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 established after 1890 are now continuously out of priority (Colorado DWR).

Agricultural producers in WD1 face uncertainty in water availability from two predominant sources. First, 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). Second, water supplies in arid regions are largely affected by climate change (Lioubimtseva, 2004). 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).

The Natural Experiment

In addition to designating water divisions, the 1969 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). 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 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

[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.

[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`.

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.

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

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

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

$$\text{Treatment} = \begin{cases} \text{Yes}, & \Delta C_d \geq 50\% \\ \text{No}, & \Delta C_d < 50\% \end{cases} \tag{9}$$

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

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

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 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

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

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 partially 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

[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.

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.

Using seasonal crop-water demands for corn, alfalfa, and wheat, we make a back-of-the-envelope calculation of the potential demand reduction for treatment structures.[10] Applying these reductions to the study area, we estimate a reduced seasonal irrigation demand of 85,000 acre-feet or 28 billion gallons of water across WD1 by 2015. 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

[10]First, we multiply the 2015 coefficient estimates 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 (Schneekloth and Andales, 2017), for an acre of each crop with flood irrigation versus sprinkler irrigation. The difference for each crop is then multiplied by the values from the first step.

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 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

[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`.

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.

Lastly, we investigate the potential impacts of 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 permanent curtailment of many groundwater rights, we control for groundwater supplemented acreage in the Sprinkler Acres and Sprinkler % models to ensure our results are largely driven by the change in surface water availability. Estimates of the groundwater supplemented acreage were omitted from the main 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 with the groundwater control variable are presented in Table 4. The only qualitative change to the results is the loss of significance for the Treatment*2005 variable for the Sprinkler Acres model. Otherwise, the longer-term trends and Sprinkler % results remain largely unaffected.

Conclusion

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 a producer's beliefs about input shortages would incentivize investment in a more

efficient technology in an agricultural context. 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 Northeast Colorado that led to a change in expectations about the availability of surface water for irrigation 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. First, 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 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 resource management implications. First, climate change and growing populations put continued stress on natural resource supplies, and beliefs will play a critical role in the future adoption of conservation practices. 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, education and public awareness campaigns that can accelerate belief revisions before the realization of severe weather disruptions may have understated long-term benefits. Better information on the future possibility of shortages can enable producers to minimize their down-side risk. Second, public agencies concerned with sustainable resource management rely on accurate demand estimates when evaluating the costs and benefits of institutional reform or infrastructure projects. Our findings emphasize that lasting trends in input use efficiency are significantly influenced by responses to extreme resource shocks. When modelling future resource demands it is important to endogenize factors such as technology adoption.

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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 %
Treat*1976	-251.5	-190.9	-0.016	-0.014
	(214.3)	(193.8)	(0.022)	(0.022)
Treat*1987	-175.7	-207.9	-0.006	-0.007
	(131.9)	(146.5)	(0.013)	(0.013)
Treat*1997	-114.1	-134.0	0.012	0.011
	(78.8)	(96.2)	(0.008)	(0.009)
Treat*2005	254.5**	-94.8	0.048***	0.033**
	(87.2)	(124.7)	(0.012)	(0.013)
Treat*2010	516.7**	354.5*	0.077***	0.070***
	(163.1)	(162.9)	(0.020)	(0.020)
Treat*2015	723.3**	624.5**	0.112***	0.108***
	(237.5)	(219.5)	(0.025)	(0.025)
County Pop.	-0.0007	-0.002	-2.11×10^{-7} *	-2.46×10^{-7}*
	(0.001)	(0.001)	(1.07×10^{-7})	(1.07×10^{-7})
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
Adjusted R^2	0.792	0.820	0.701	0.707

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

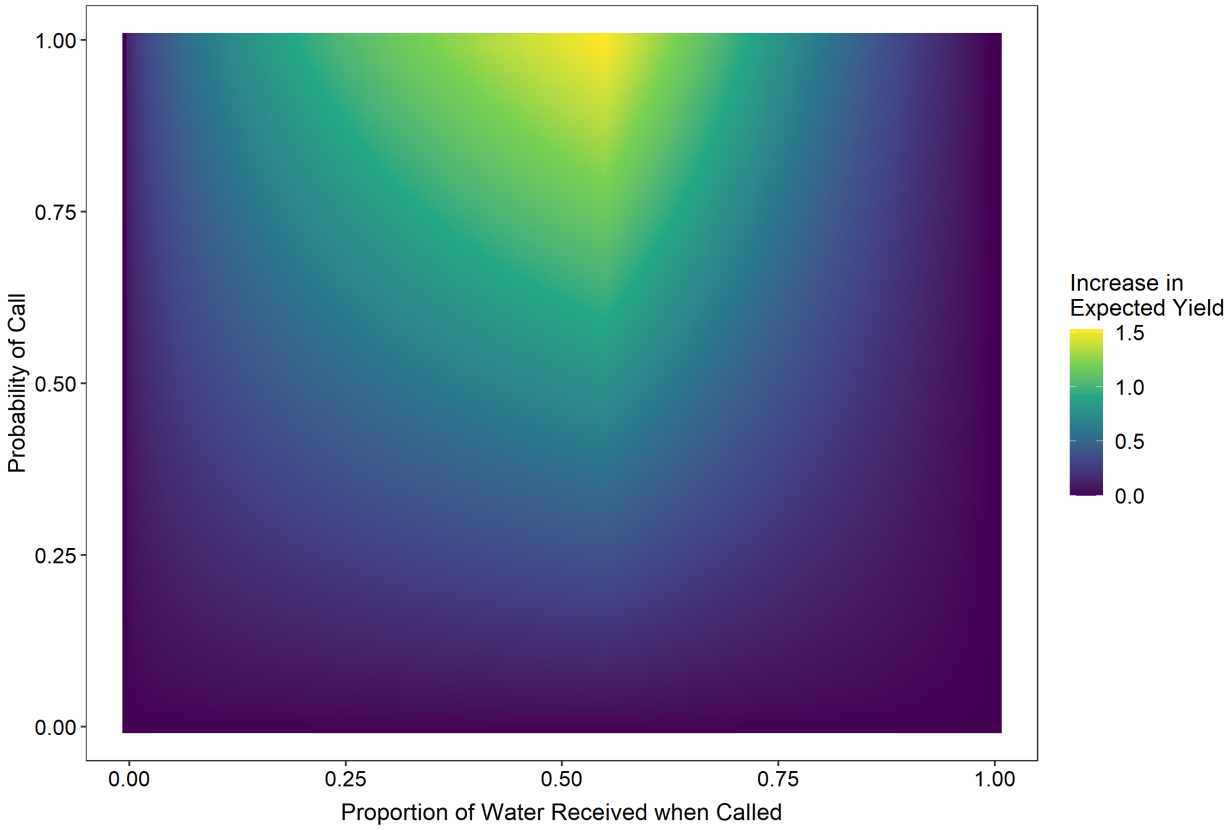


Figure 1: How Beliefs Impact the Gross Benefit of Investment

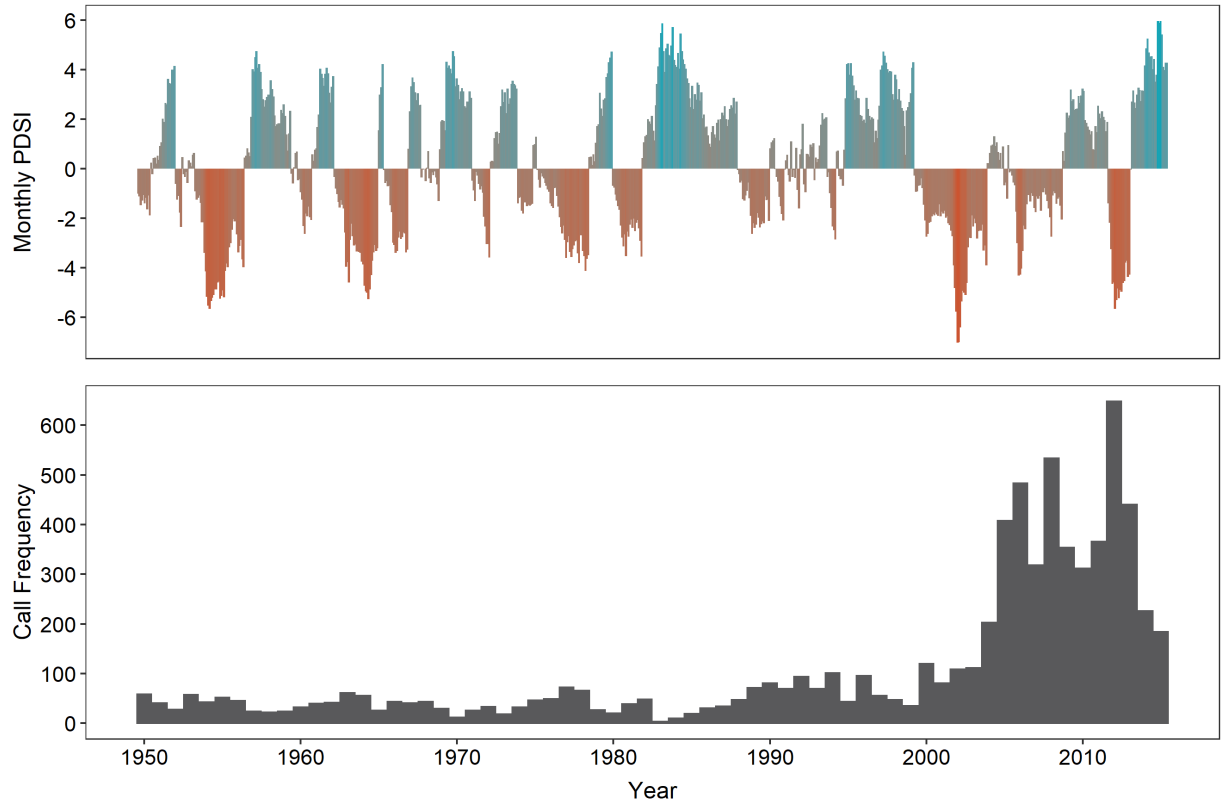


Figure 2: Monthly PDSI and Frequency of Calls by State Engineer, Colorado Water Division 1

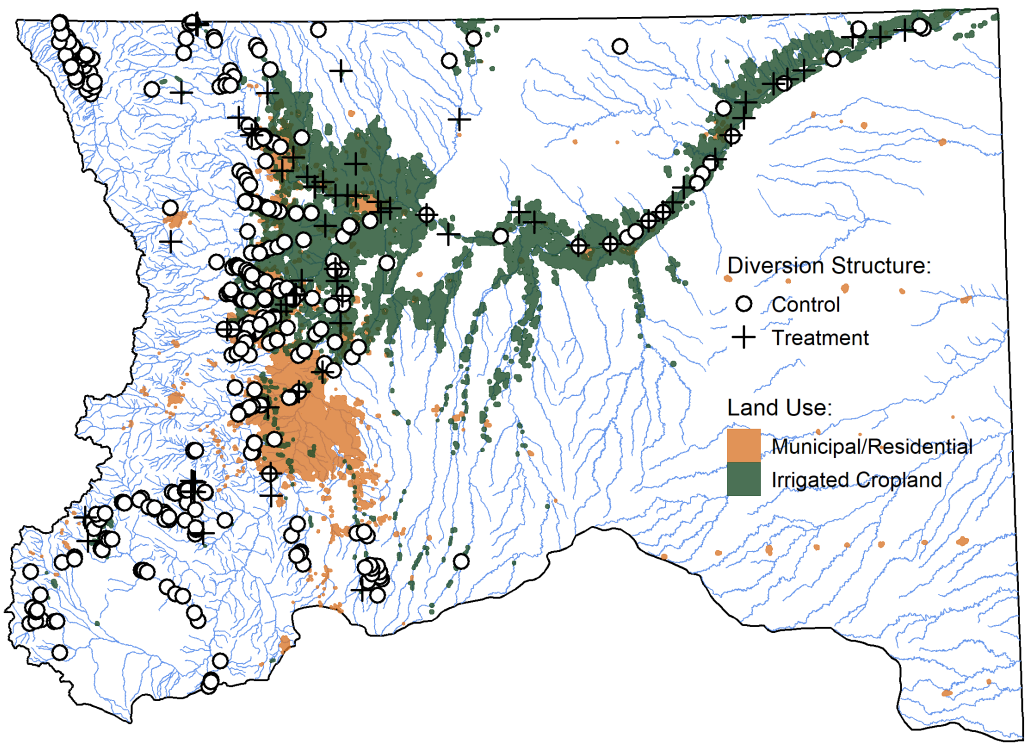


Figure 3: Treatment and Control Diversion Structure Map, Colorado Water Division 1

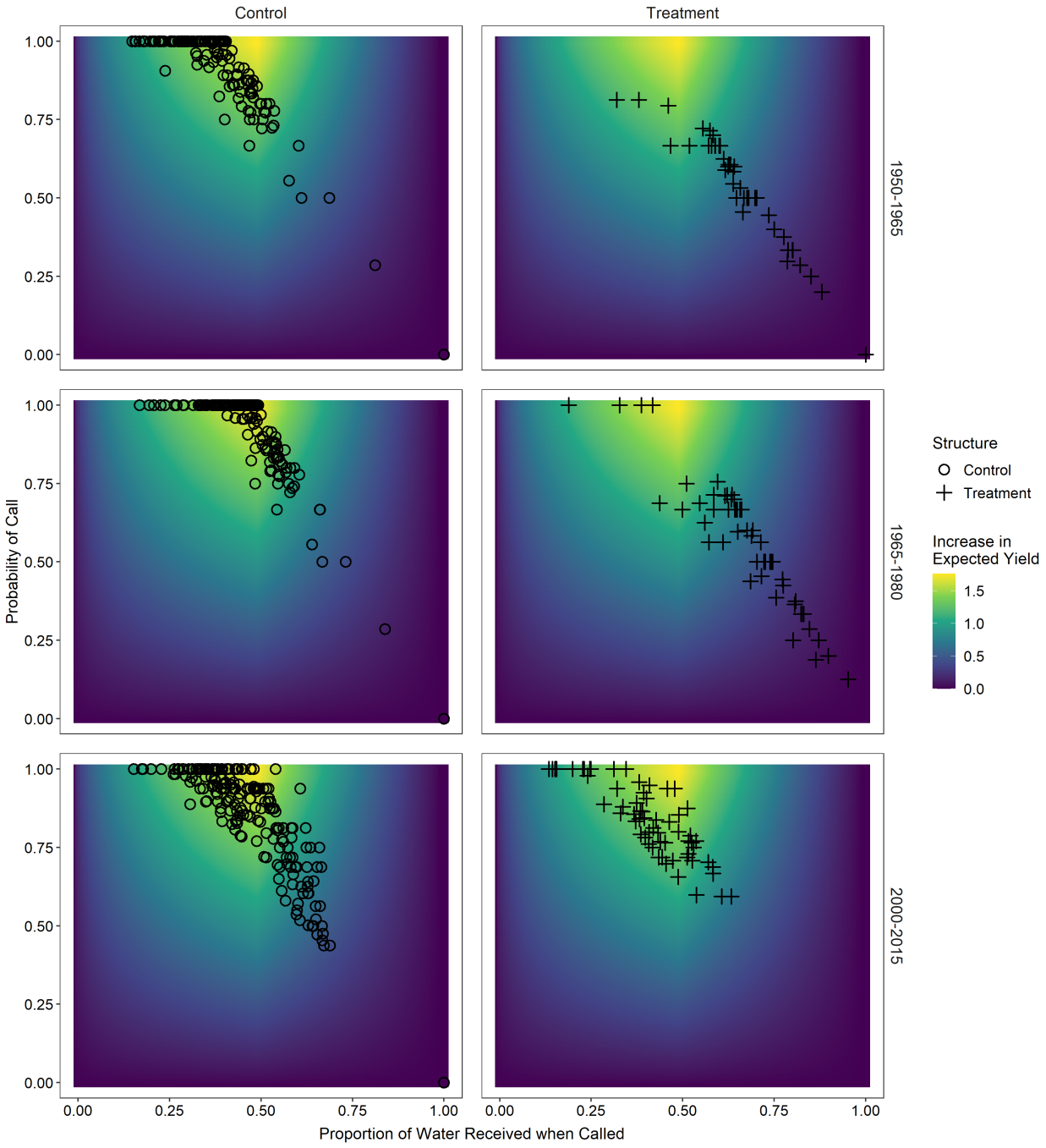


Figure 4: Estimated Belief Parameters for Control versus Treatment Diversion Structures

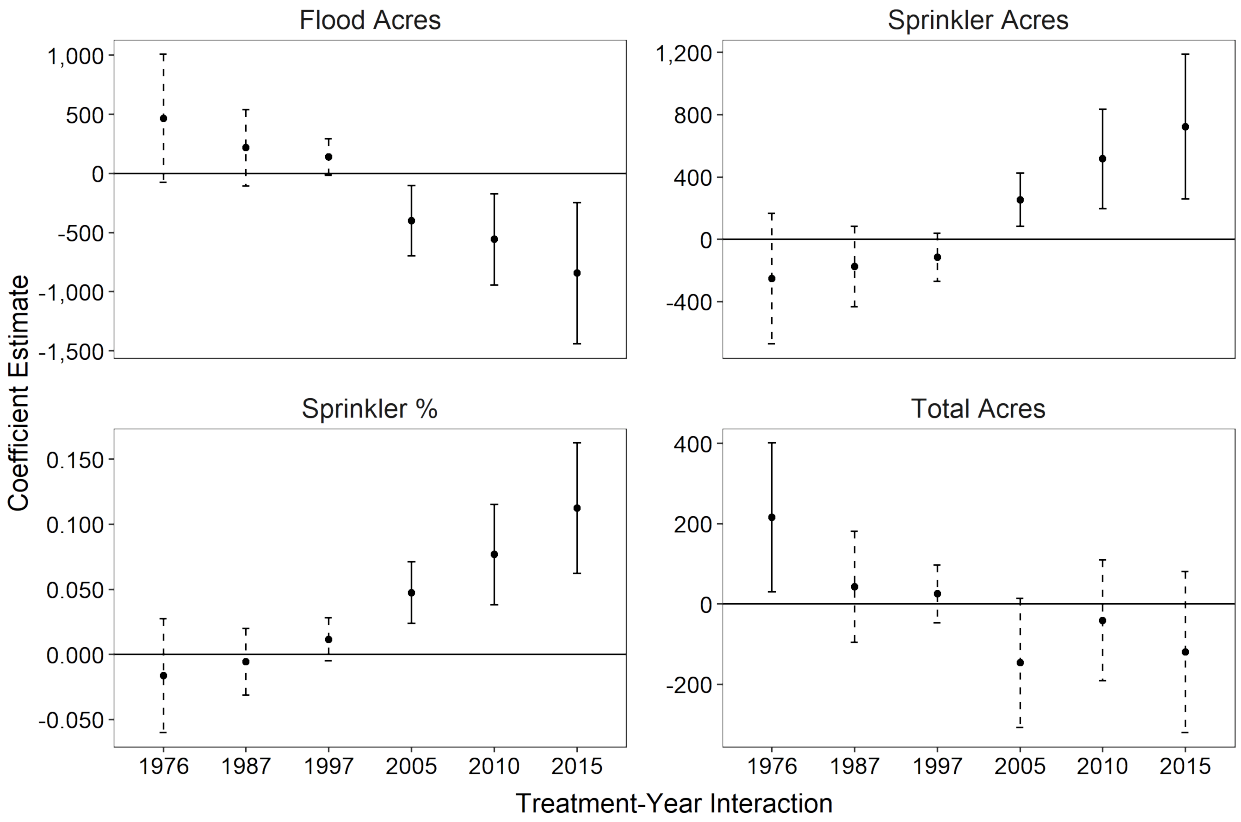


Figure 5: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Irrigation Practices

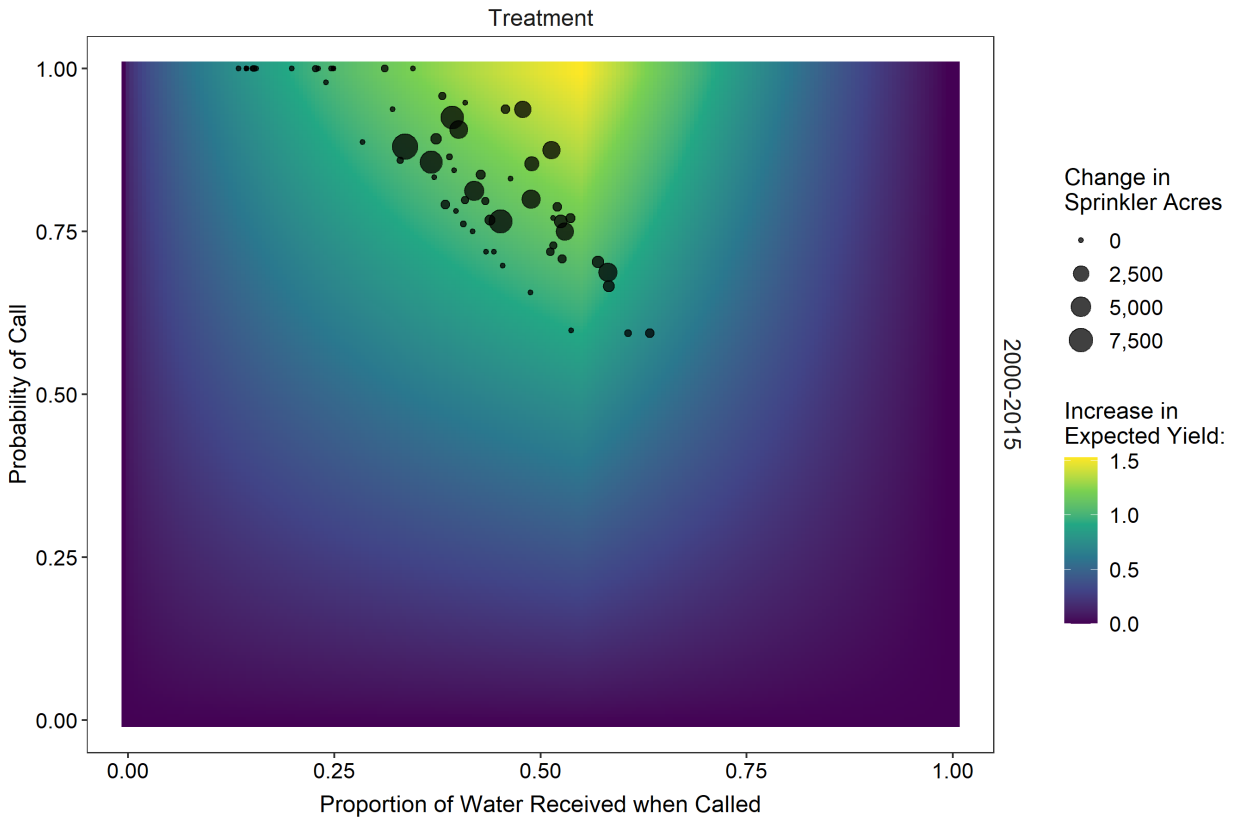


Figure 6: Nonlinear Impacts of Beliefs on the Adoption of Sprinkler Technology, Total Sprinkler Acreage

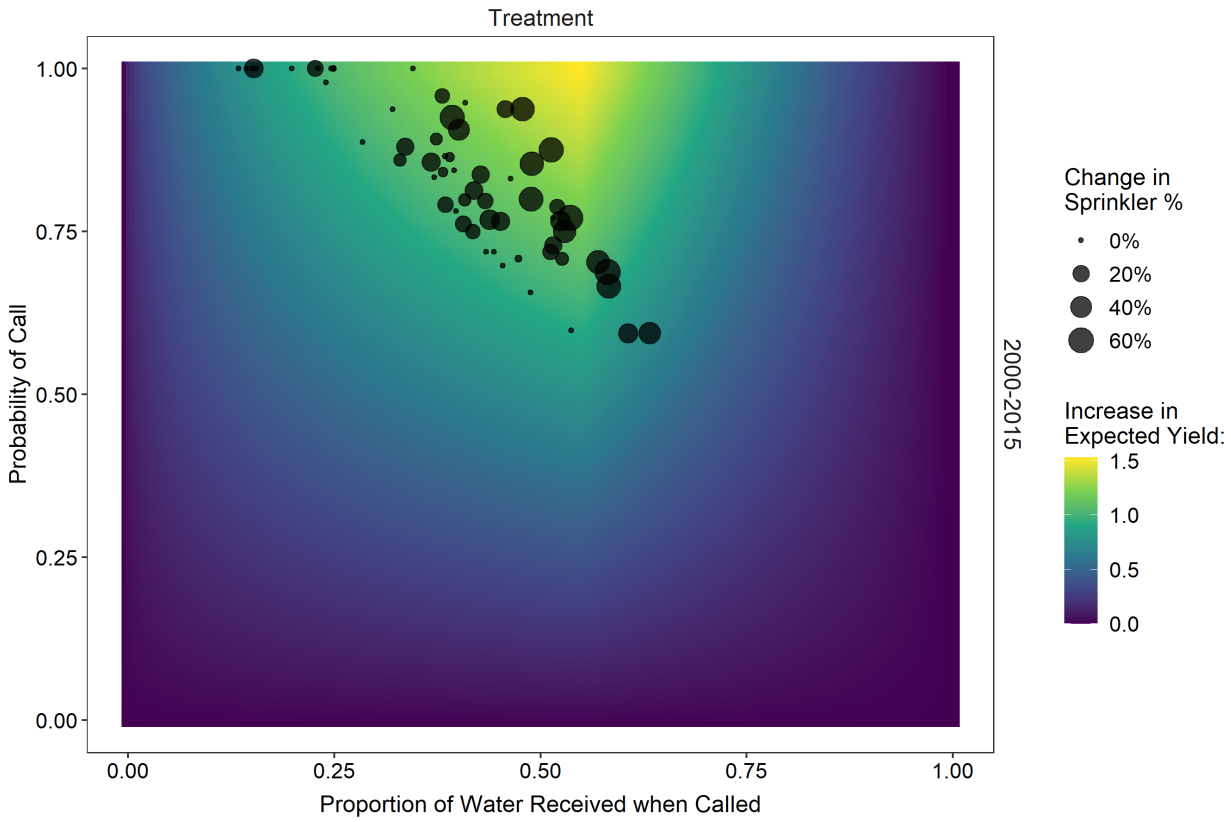


Figure 7: Nonlinear Impacts of Beliefs on the Adoption of Sprinkler Technology, Sprinkler Acreage as a Percentage of Total Acreage

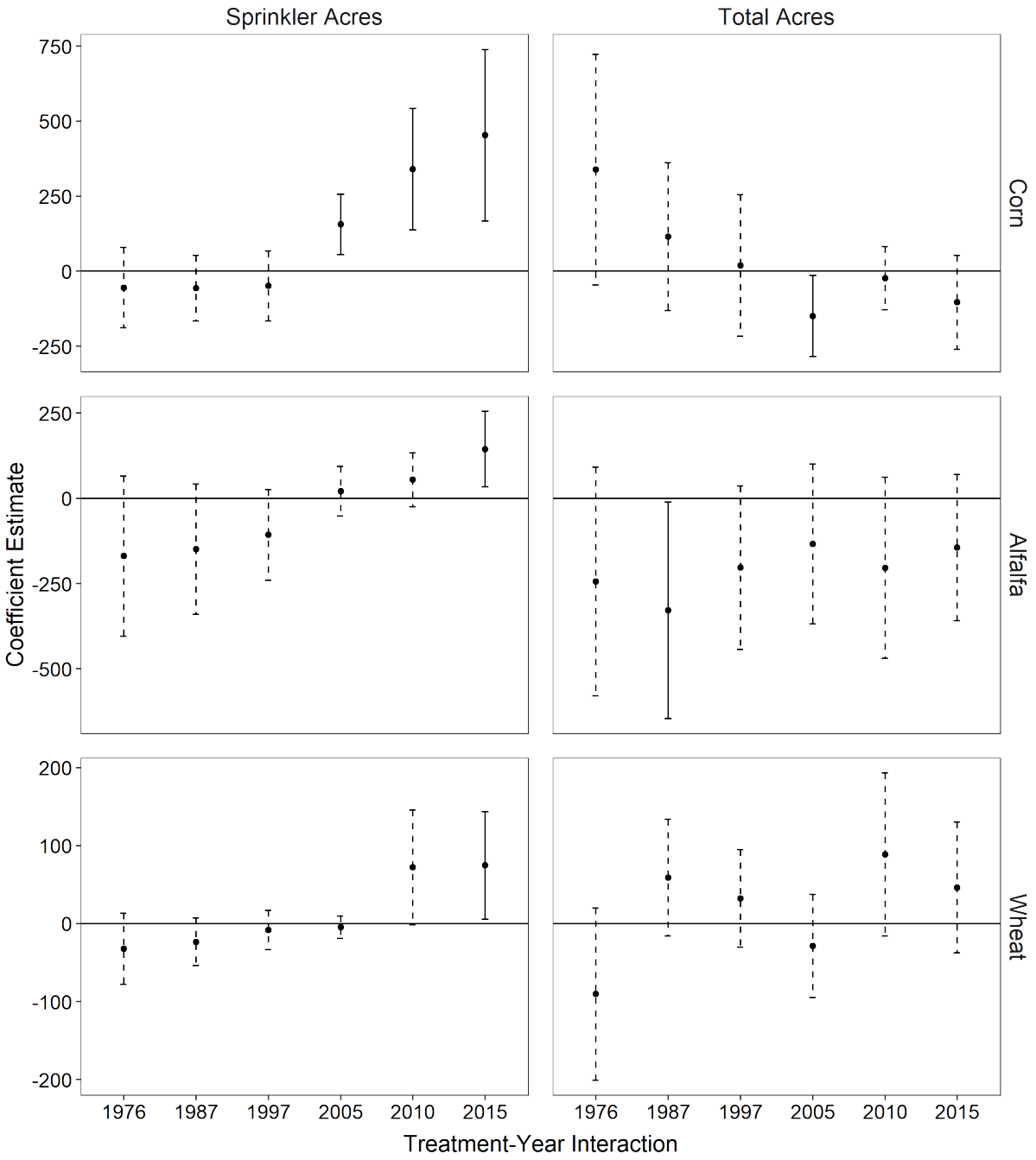


Figure 8: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Crop Choice

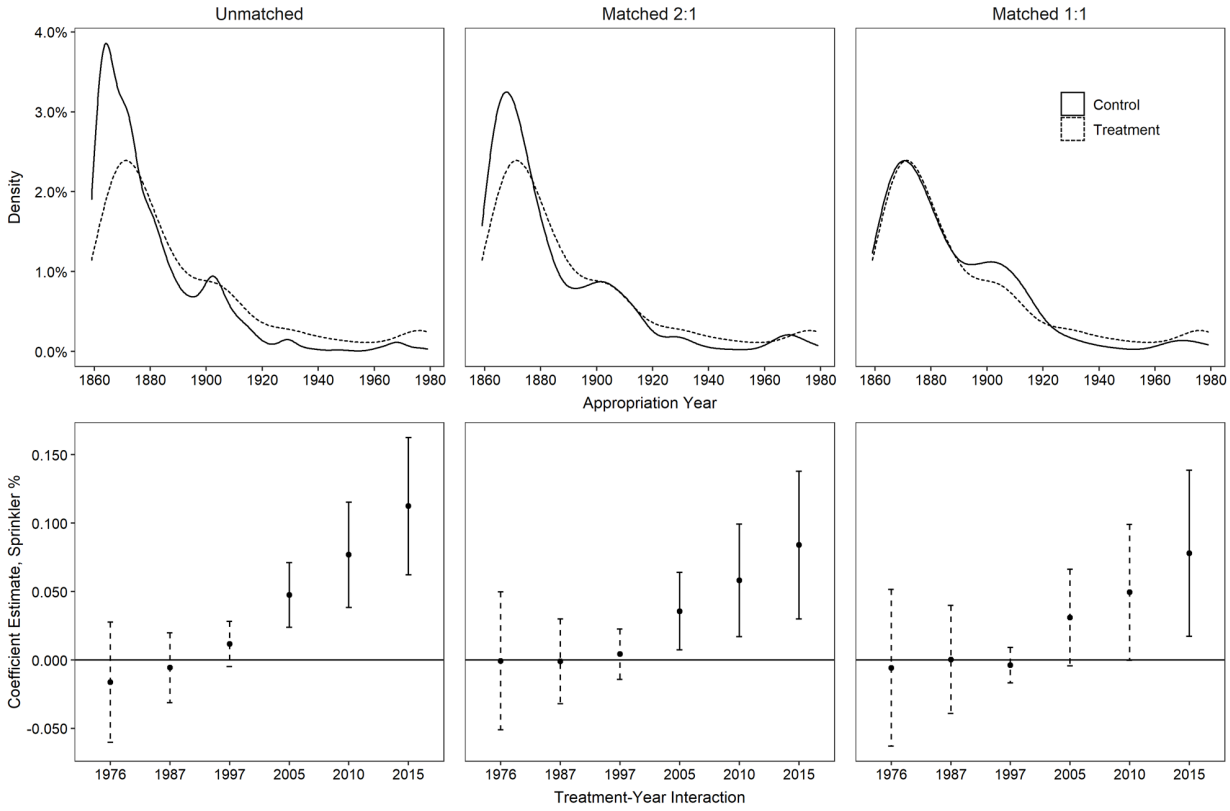


Figure 9: Difference-in-Difference Estimations Before and After Propensity Score Matching, Sprinkler %

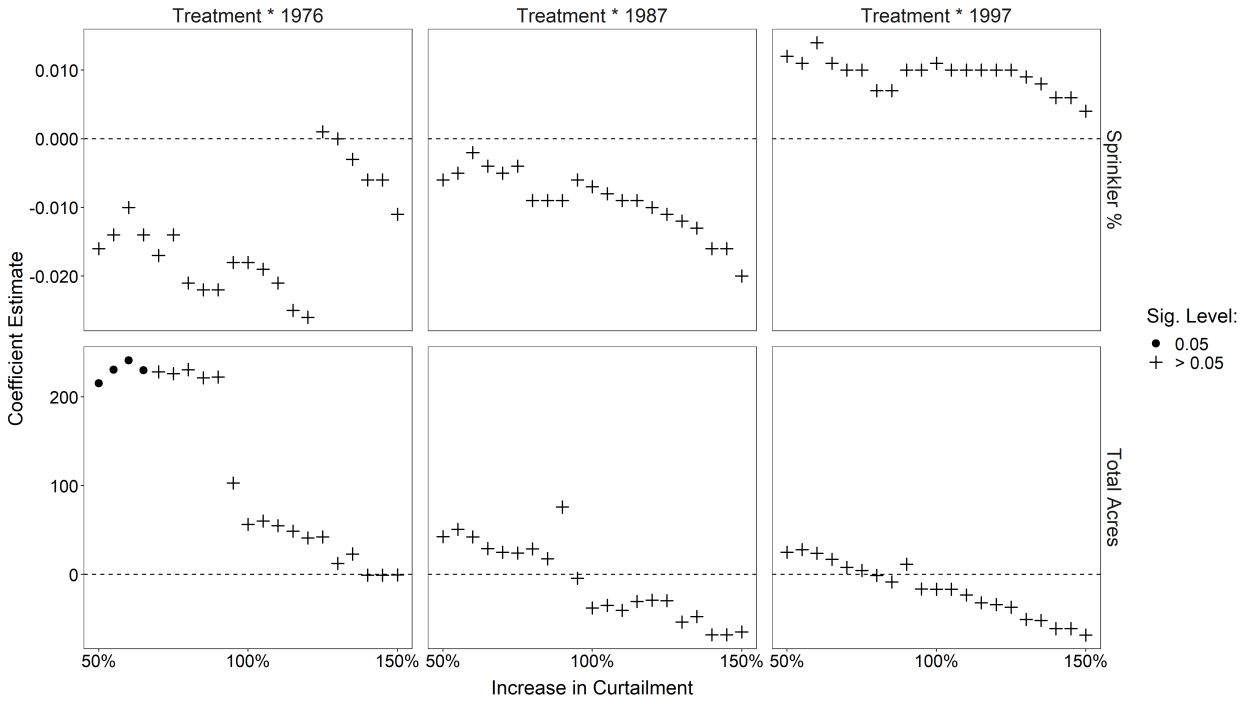


Figure 10: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Pre-Treatment



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

Appendix

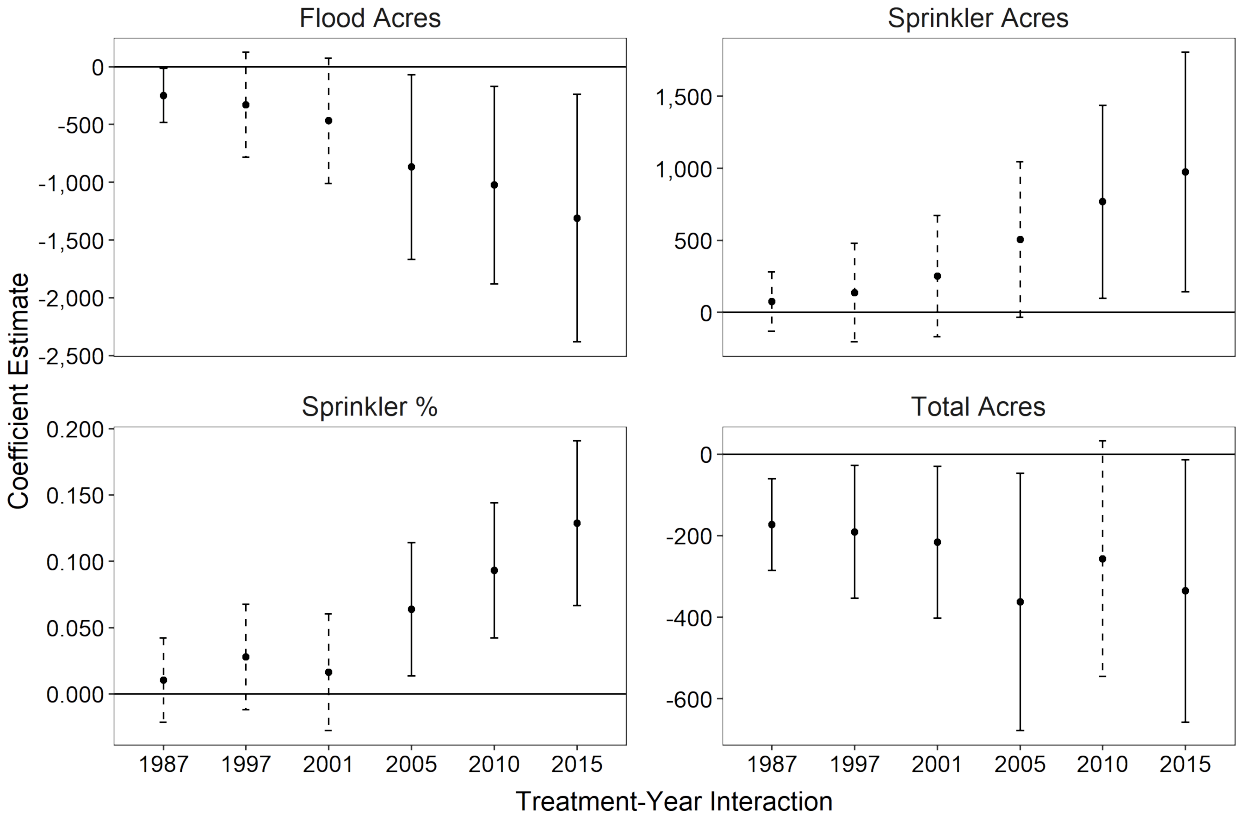


Figure A1: Difference-in-Difference Estimations, Reference Year 1976

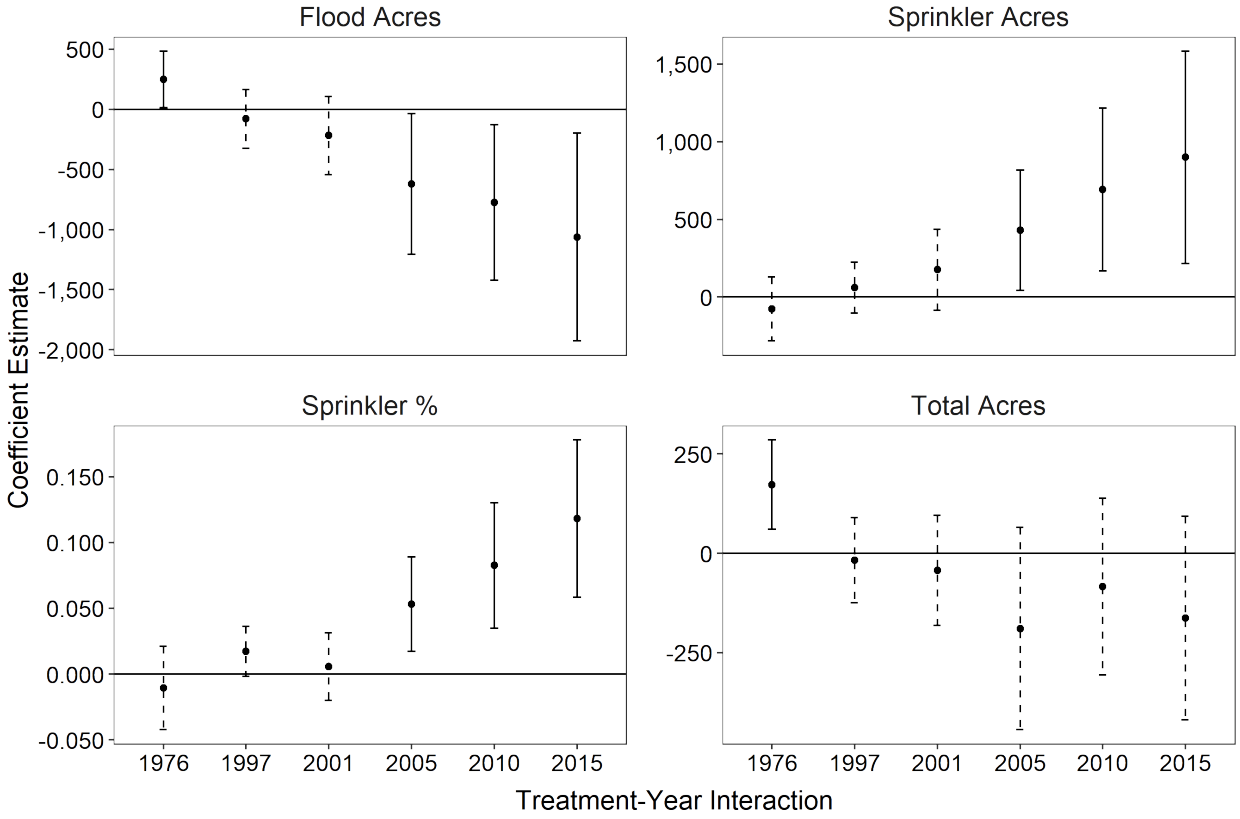


Figure A2: Difference-in-Difference Estimations, Reference Year 1987

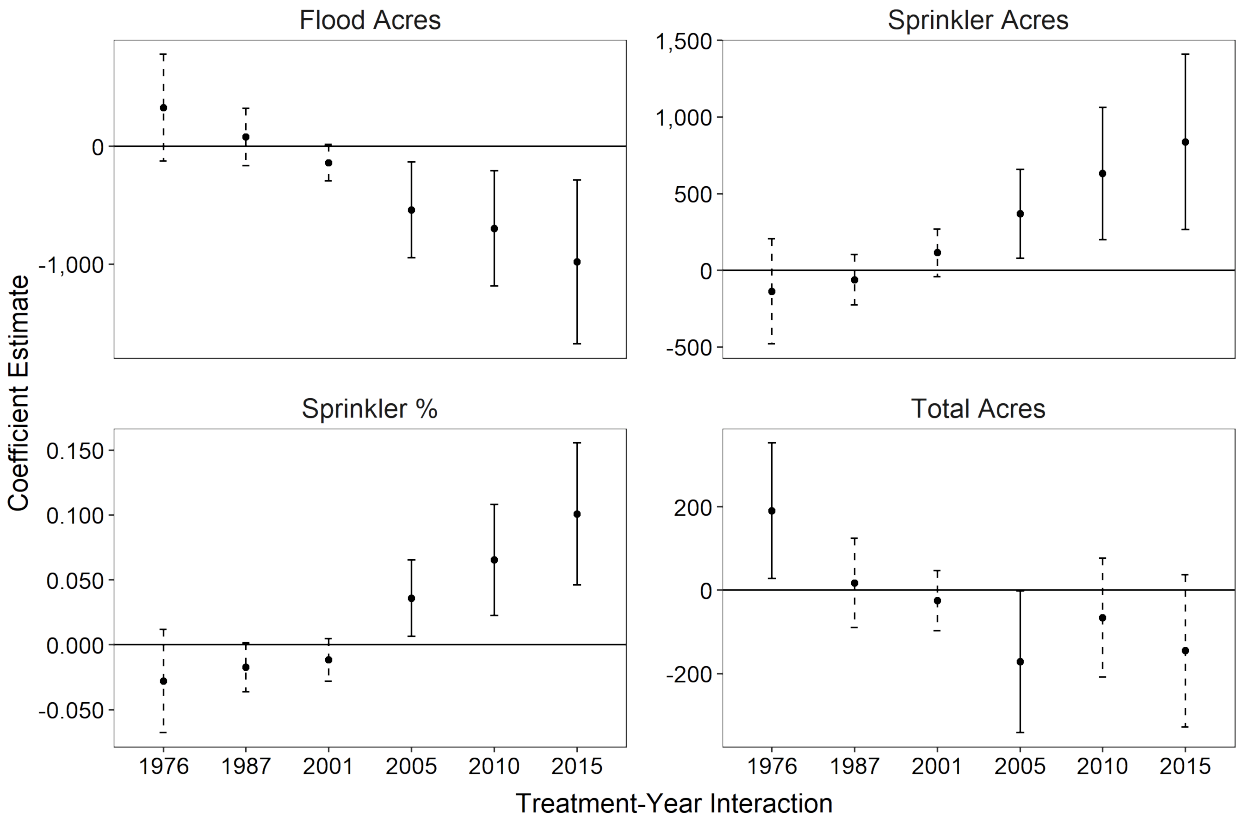


Figure A3: Difference-in-Difference Estimations, Reference Year 1997