Perceived Water Scarcity and Irrigation Technology Adoption

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July 19, 2022

Abstract

Agricultural producers make investment decisions based on expectations of future returns. This article investigates how changes in perceptions about input availability affects the adoption of conservation practices. We develop a theoretical model to examine how a producer's perception of water shortages influences investment in more efficient irrigation technologies. Using publicly available data on water rights and irrigated cropland, we construct a novel dataset to empirically identify the impact of changing perceptions 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. It is estimated 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 so by changes in surface water availability than groundwater. This analysis provides useful insight into the role of expectations in incentivizing adaptation to water scarcity in irrigated agriculture.

Keywords: prior appropriation, water scarcity, drought, irrigation technology adoption

JEL Codes: Q15, Q25, D83

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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 describes a shift in the underlying distribution of weather patterns over a long period of time. Shifting temperature and precipitation patterns are expected to contribute to increased water scarcity which poses a threat to food production (Mancosu et al., 2015). Meeting the needs of expanding populations depends on the ability of industries and governments to adapt. This is particularly relevant in arid regions, where water supplies are expected to be intensely affected by climate change (Lioubimtseva, 2004) and agriculture is often dependent on irrigation. For areas that rely on 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). As overall water availability changes, maintaining agricultural output will depend on how producers adapt. Adopting water conservation strategies is one possible mechanism.

Understanding what motivates producers to conserve water resources is important for future planning. 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 perceptions 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 change perceptions about scarcity, and subsequently change behavior, can be difficult. Some literature suggests that personally experiencing an extreme weather event can change climate change perceptions and increase 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 cross-sectional survey data and cannot track behavioral changes over time. Overall, literature investigating how perceptions impact behavior using observational, non-survey data is scant. In this article, we explore how changing perceptions about water scarcity affects conservation investment decisions for agricultural producers. A simple theoretical framework is developed to demonstrate the conditions under which a producer's perception of water availability 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.

Perceptions about water availability play a critical role in decision-making for producers that are dependent on irrigation. In the United States, western states (the American West) 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, which reduces snowpack depth and changes the seasonality of runoff (EPA, 2016). Several studies have examined recent hydrological changes in the American West, 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 and evaporation trends, 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 macro-scale 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 American West 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 have a belief about the probability distribution of input shocks. When considering multi-year investments in water conservation technologies, a farmer likely assesses of the probability of a water shortage. Ji and Cobourn (2021) provide an intuitive framework of expectation formation, proposing that perceptions about weather—or supply conditions—develop with an increased bias toward recent events. Therefore, experiencing a disproportionately extreme event triggers a larger revision to expectations, 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 (i.e., yearly planting decisions), our attention lies on long-run responses (i.e., investment in infrastructure). Our novel 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 perceptions 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 develop a theoretical model to analyze the conditions under which an agricultural producer's perception 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 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 when 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 perceptions are particularly applicable to the American West, 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 perceptions about the reliability of a water supply, which allows us to measure how those 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 are determined by water right curtailments during the early 2000s shock relative to historical droughts. Results of a difference-in-difference analysis 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, cropland with corn experienced the largest increases in irrigation efficiency improvements 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 changes in groundwater use did not differ substantially between treatment and control groups beyond years immediately following the shock. 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 perceptions and conservation investment behavior.

The remainder of the article is organized as follows. First, we describe a theoretical framework used to analyze the impact of perceptions on irrigation technology adoption in the context of prior appropriation, which is the dominant water allocation system in the American West. 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 modeling approach. In the final sections we present the estimation results, analyze their robustness, and conclude by discussing policy implications.

Theoretical Framework

When adapting to increasing water scarcity, farmers face a menu of potential strategies to reduce their overall water dependency. Drought-tolerant crop varieties and species can be planted in lieu of water-intensive ones. Deficit irrigation on large quantities of land or increased irrigation on a reduced quantity of land offer opportunities for water savings. Technologies that harvest and store water or reduce conveyance losses can increase average supplies. Improving the application efficiency of an irrigation system can reduce the amount of diverted water necessary to achieve full evapotranspiration. The advent of water markets and water-sharing agreements allow farmers to diversify their income through selling water or to hedge against drought risk by buying water. In general, the actual costs and benefits of different adaptation strategies from this suite of options depends on a farmer's characteristics, such as geographic location. However, farmers' *expected* costs and benefits, which ultimately drive adoption decisions, vary largely according to perceptions about water scarcity. Otherwise similar farmers with different perceptions may exhibit a vastly different willingness to invest in practices that reduce water use. In the following theoretical framework, we focus solely on how perceptions drive the decision to improve irrigation efficiency. Although our theoretical model is presented in the context of a producer evaluating the expected benefits from adopting an irrigation technology, the findings apply more generally with respect to how perceptions of scarcity influence producer decisions to invest in technologies and/or practices that improve water use efficiency.

To examine the impact of perceptions 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 perceptions about input availability on the investment decision.

Water allocation in most of the American West 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 first 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 increase irrigation efficiency from

[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.

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 assumes a 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 his perception of 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] 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

[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.

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 has $\theta = 0$ and an expected gross benefit equal to zero.

Parameter Simulations

We now examine how perceptions of θ and δ 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 parameters 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 perceptions (Figure 1). Each point on the heat map corresponds to a possible combination of θ (probability of a call) and δ (magnitude of shortage) for an individual producer. The background shading at each point corresponds to the gross benefit, or increase in expected yield, associated with that combination of θ and δ. Darker (lighter) areas are associated with lower (higher) gross benefits, so a change that results in movement from a dark area to a lighter area would result in an increase in benefit. The impact of θ is straightforward and monotonic. Pick one point along the horizontal axis and hold δ constant, and each point directly above (increasing θ) lies on a lighter area on the map. In other words, as a possible call becomes more likely, the benefit of improving water application efficiency increases monotonically. If the perceived probability of a call is 0, there is no incentive to invest.

The impact of δ is less straightforward. When holding θ constant and moving along points from left to right, the benefit is greatest around $\delta = 0.55$, after which the benefit decreases. 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 perception 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 about half 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 considerable heterogeneity in producers across the American West, 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. 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 revealed 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

[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.

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.[4] 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. 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.

[4]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`.

Data and Modeling Approach

To exploit the exogenous 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.[5] 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 a 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 a perception 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

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

the recent 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 to the 50% cutoff is examined in the first section of the Appendix.

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 investigate if treatment structures are 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 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, 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 are not statistically distinguishable from zero prior to the shock. This provides suggestive evidence that the treatment and control groups have parallel trends. We present coefficients for the treatment variables graphically in Figure 4, with 95% confidence intervals, to check for the existence of differential 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.

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 in irrigated acres across the basin 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 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 5, again with 95% confidence intervals, and cluster-robust standard errors are available in Table 3. Regression results indicate that corn was the crop that experienced the biggest increase in sprinkler-irrigated land as a result of the shock. On average, corn acreage accounted for 60-65% of the increase in sprinkler acreage for all post-treatment years.[6] 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. This suggests that adjustments to the change in relative scarcity were made on the intensive margin (adjusting water application per acre) rather than the extensive margin (retiring cropland).

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

[6] This was estimated by dividing the coefficient estimates from the corn-specific Sprinkler Acres model (Table 3, column 2) by the coefficient estimates from the total Sprinkler Acres model (Table 2, column 2).

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 model 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.[7] The difference for each crop is then multiplied by the values from the first step. In total, we estimate a potential reduced seasonal irrigation demand for water diversions 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.[8]

In Figure 4, 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.[9] Results from the matching exercise are presented in Figure 6. 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 6 displays a smoothed density curve for the total sample and the two matched samples, and the second

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

[8] This comparison is made only to provide perspective on the volume of water. According to Colorado water law, water "saved" via irrigation efficiency gains cannot be reused or sold.

[9] 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.

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. Additional robustness checks and analysis relating to treatment design, model specification, and nonlinear impacts from the shock can be found in the first three sections of the Appendix, respectively.

Conclusion and Policy Implications

In this article, we explore the impact of perceived input scarcity on conservation investment decisions. We develop a theoretical model to examine the conditions under which an agricultural producer's perception of water shortages would incentivize investment in a more efficient irrigation technology. A numerical exercise is used to demonstrate a range of perceptions 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 unprecedented 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 trigger investment in efficiency due to changes in perceptions.

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. For example, 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.

In Colorado, water rights can be bought and sold, and a distinct feature of our study area is the presence of active water markets. Most market activity consists of municipal and industrial buyers and agricultural sellers. Some rights were undoubtedly traded during our study period, which we are unable to track. We can only observe the decreed uses of a particular water right as they exist today, and 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. Although we cannot identify which water rights were sold, we find that changes in total irrigated acreage did not differ substantially between treatment and control groups. This provides some evidence that agricultural water rights are being sold at similar rates across all diversion structures, regardless of the heterogeneous impacts of the shock.

Concerning water right transactions, improving irrigation efficiency does not generally reduce the value of a water right. One aspect of prior appropriation is that water rights may be forfeited if the owner consistently fails to apply the water to a beneficial use, otherwise known as "use it or lose it." This component however only applies to the consumptive use determined by the water right. In the case of a farmer, the consumptive use of his water right is determined by the annual documented evapotranspiration of his crops, not the total amount of water diverted. Since improving irrigation efficiency only reduces the amount necessary for diversion and not the beneficial, consumptive use, the water right's value should not be affected. In the case of a water right transfer, the transferee buys only the right to the consumptive use regardless of the transferor's former diversion amounts. In general, the "use it or lose it" rule is not a true barrier to improving irrigation efficiency, although it is potentially perceived that way by some (Waskom et al., 2016).

Another important characteristic of our study area is that all surface water and most groundwater resources are administered similarly under prior appropriation, which is not uniformly the case across the American West. 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. Groundwater aquifers are often exhaustible in practice, 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 may increase the longevity of agricultural production under climate change.

Lastly, 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 efficient 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.

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 perceptions will play a critical role in the future adoption of conservation practices in agriculture. Neglecting how costs and benefits are perceived 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 perceptions about necessity. If the latter is the driving factor, efforts to accelerate revisions to perceptions to align with actual shortage distributions, before the realization of costly 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 perceptions 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 changes. If climate change is perceived as a real risk, communicating the 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 changes in perceptions, 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.

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	$-2.11 \times 10^{-7\,*}$	$-2.46 \times 10^{-7*}$	-.0007**
	(0.001)	(0.001)	(1.07×10^{-7})	(1.07×10^{-7})	(.0002)
GW Acres	-	-1.32***	-	$-5.38 \times 10^{-5***}$	-
	-	(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

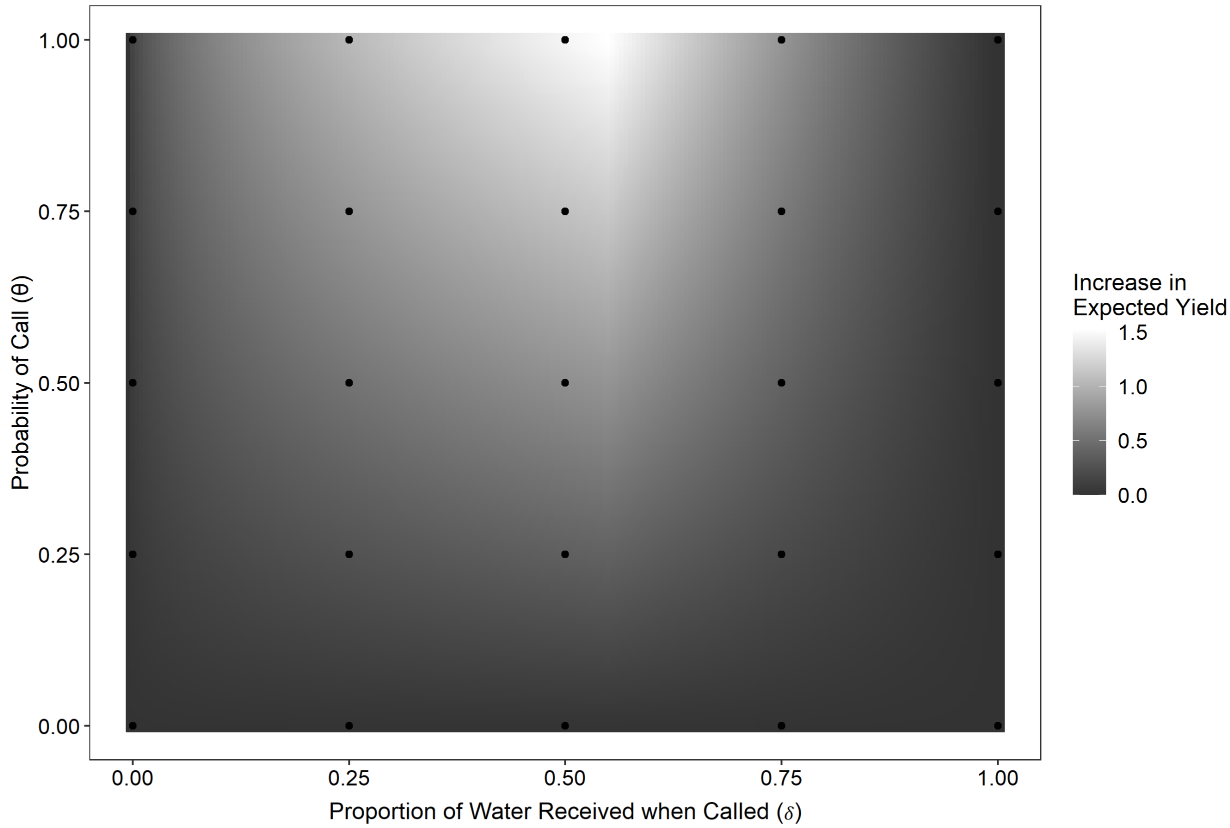

Figure 1: How Perceptions Impact the Gross Benefit of Investment

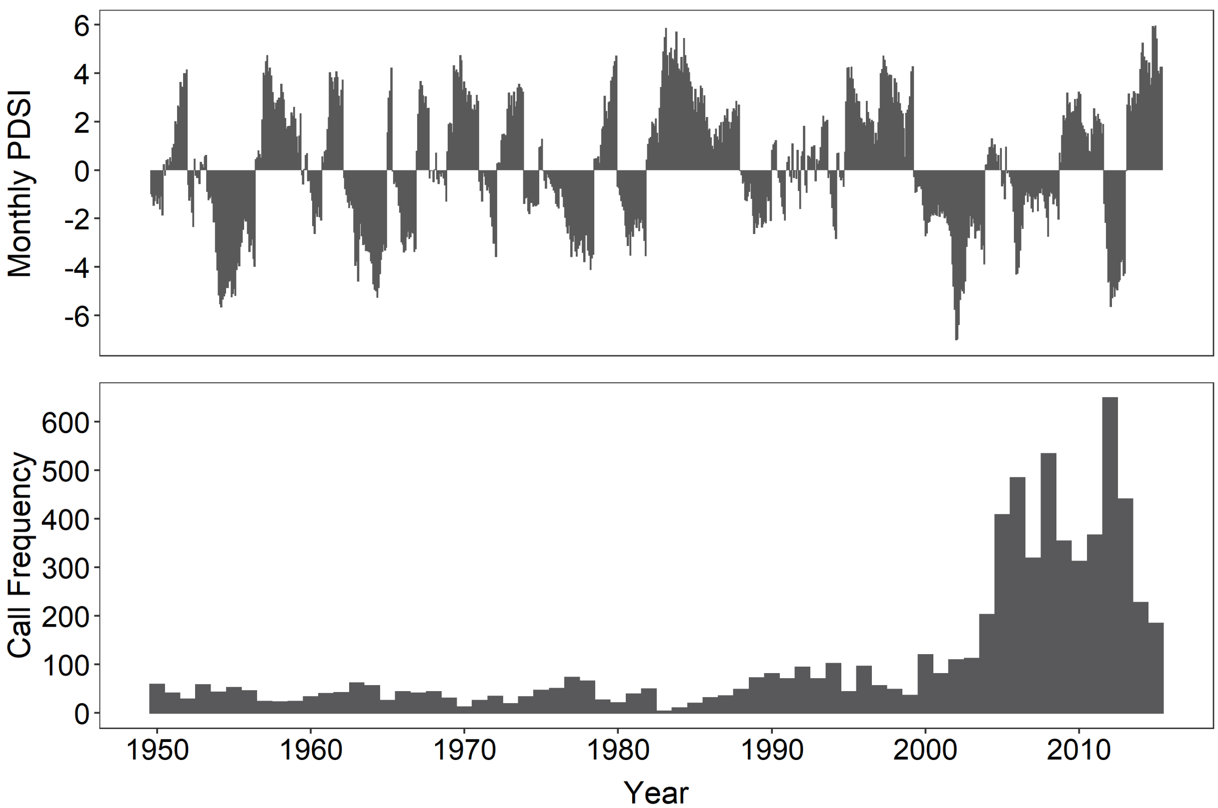

Figure 2: Monthly PDSI and Frequency of Calls by State Engineer, Colorado Water Division 1

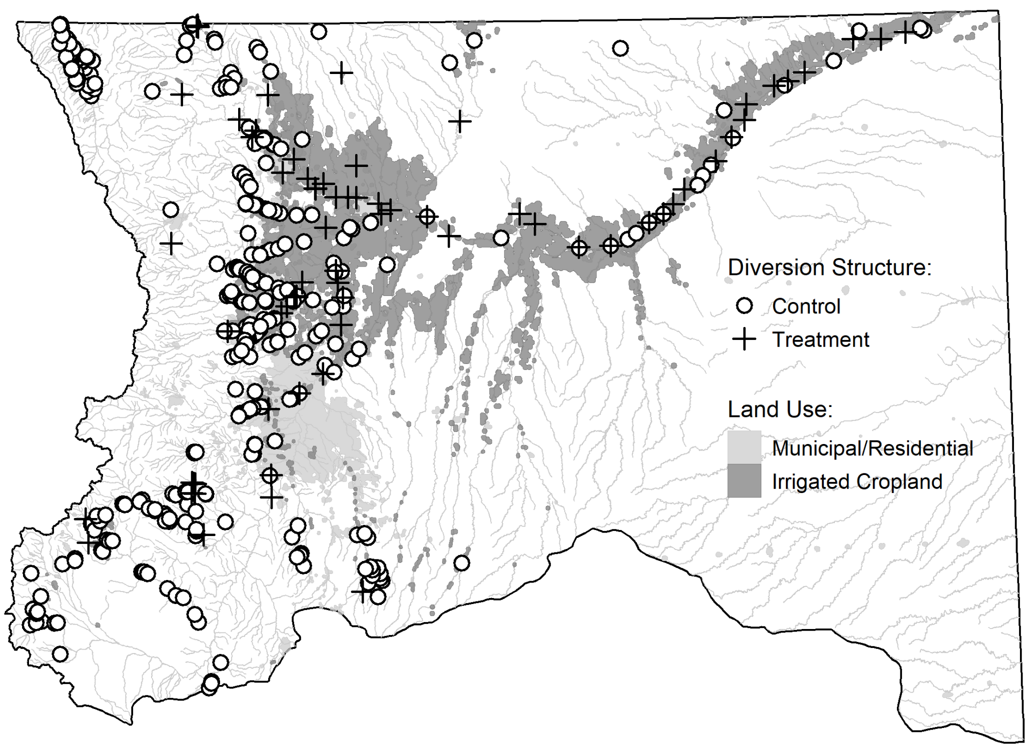

Figure 3: Treatment and Control Diversion Structure Map, Colorado Water Division 1

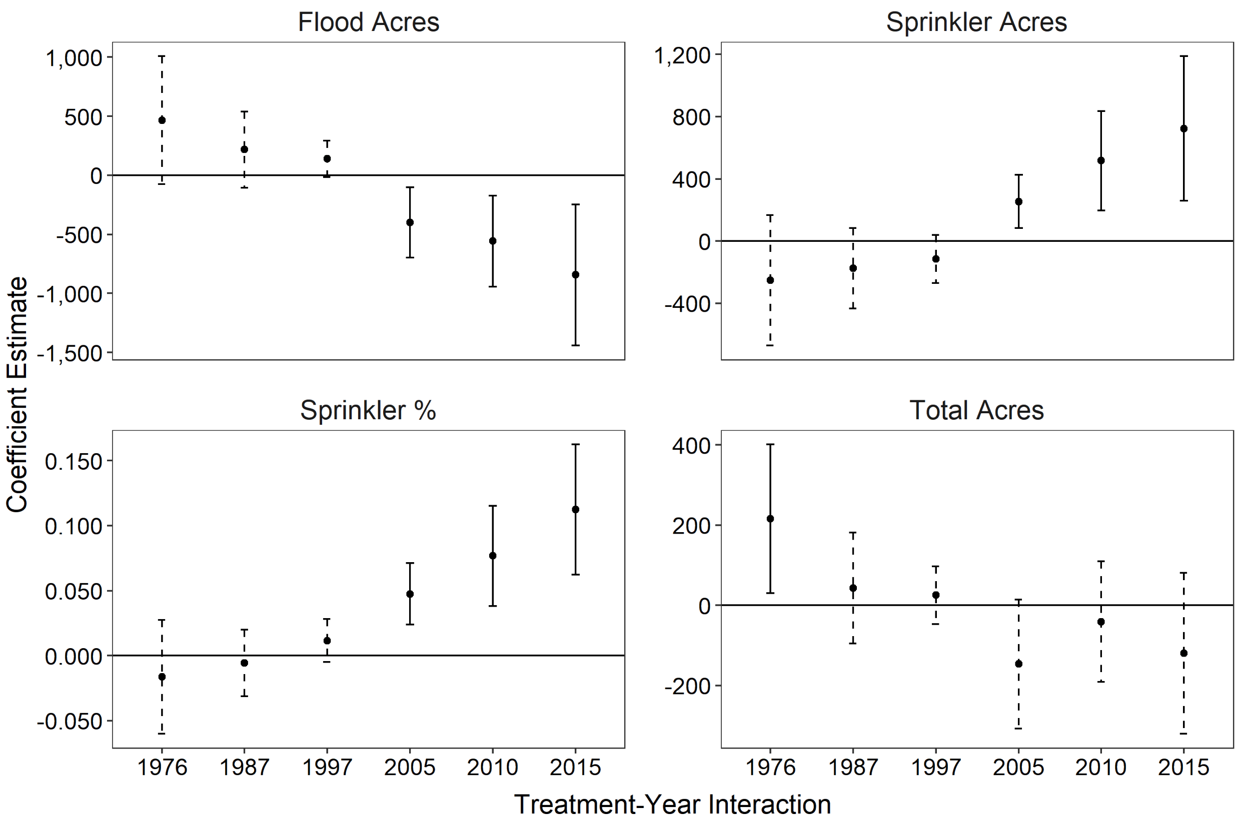

Figure 4: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Irrigation Practices

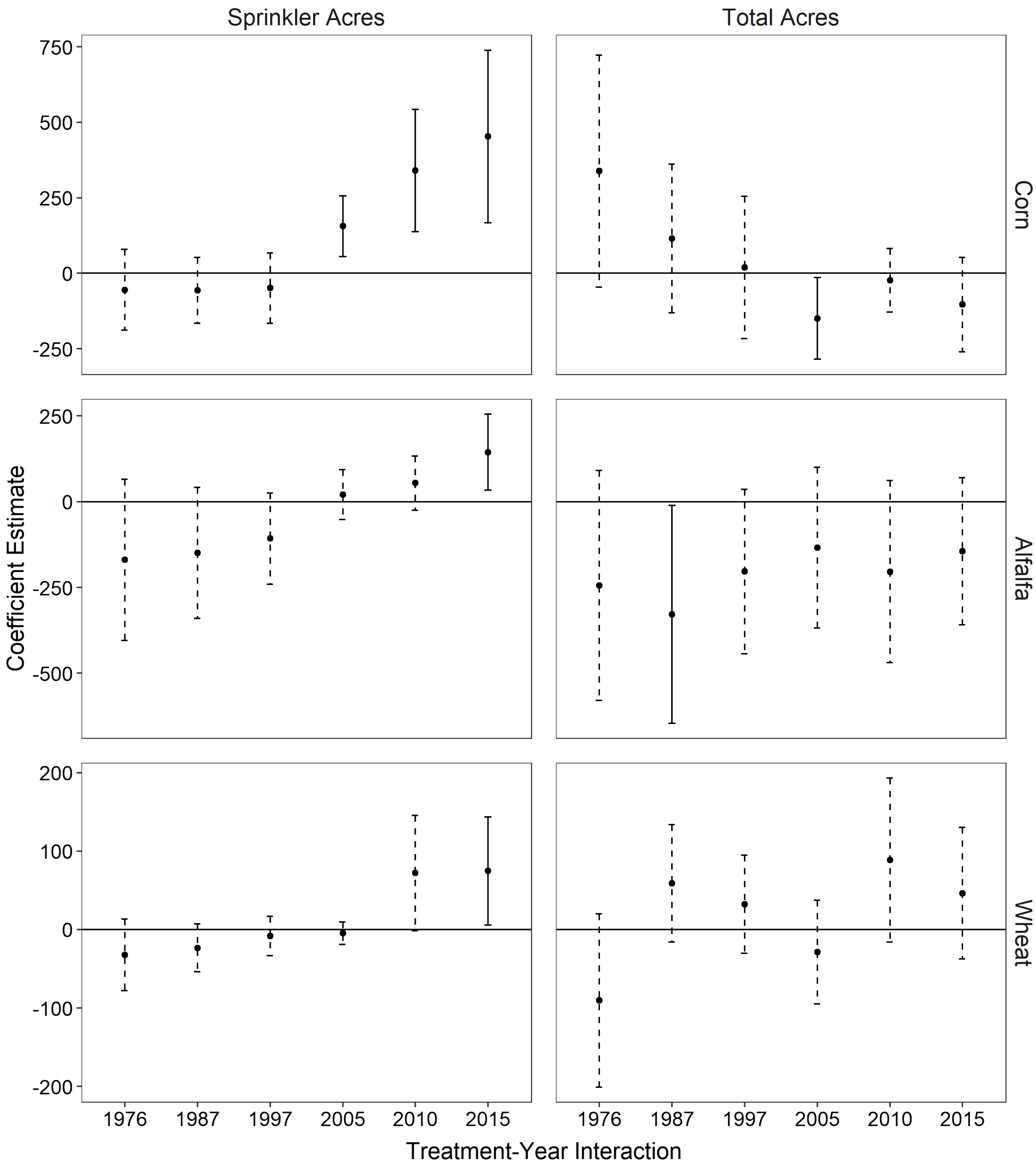

Figure 5: Difference-in-Difference Estimations of the Impact of Drought and Institutional Change on Crop Choice

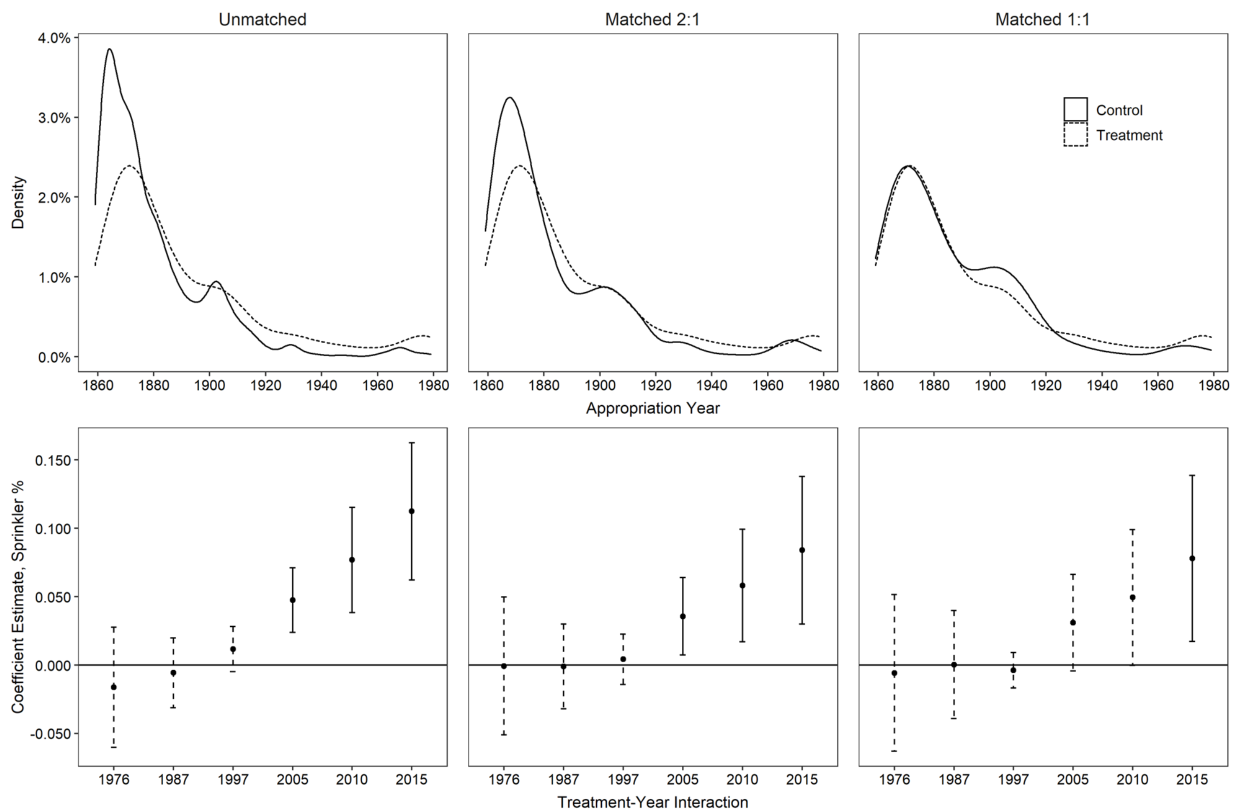

Figure 6: Difference-in-Difference Estimations Before and After Propensity Score Matching, Sprinkler %

Appendix

Scrutinizing the Treatment Design

To further investigate our treatment design, we approximate the parameters defined in the theoretical model and impose the values on the heat map (Figure A1). Although treatment and control groups were determined by impacts during only drought years, we estimate perceptions using three 16-year periods that include both dry and wet years. Drought shocks are random, and a producer would develop perceptions 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 A1 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 perceived water availability. The relatively stable parameter estimates for the control group indicate they did not experience the drought shock to the same degree, as compared to prior droughts, as the treatment group.

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 A2 and Figure A3, 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.

Addressing Threats to Identification

Here we address the possibility of multiple or staggered treatments. In our main econometric specification, we leverage the shift in the call regime as a singular treatment event. However, drought varies in intensity from year to year, and it is possible that some treatment structures were impacted differently in years post-2002. If treatments are heterogeneous and staggered across time, then our model would be misspecified, and we would instead need to employ a difference-in-difference design suitable for estimating average treatment effects with two-way fixed effects and heterogeneous treatments (e.g., Callaway and Sant'Anna, 2021). We explore this possibility graphically and further clarify the aim of our current treatment design. We first draw attention to the bottom right panel of Figure A1, which displays parameter estimates from the theoretical model for all treatment structures for the 2000-2015 time period. We find that all treatment structures move similarly on the heat map, in aggregate. Disaggregating to yearly impacts, Figure A4 shows the average days under curtailment for every diversion structure in our sample by year. Each point represents the average number of days under curtailment across all water rights associated with a given structure in that year. Grey points correspond to dry years (PDSI < 0) and black points correspond to wet years (PDSI > 0). From the bottom panel of Figure A4, it appears that treatment structures are consistently curtailed more in dry years post-2002 than any dry year previous. Although calls at different treatment structures may have varied across years, we argue that our treatment design aims to capture the singular and systematic shift in the way calls are administered post-2002. In other words, the treatment captures a change in perceptions about water supply certainty due to a distributional change in the call regime rather than year to year drought severity, which makes our model specification appropriate.

Next, we examine the robustness of our econometric results to adjustment of the reference year. The reference year of 2001 was chosen as it is the most recent year prior to treatment, but its omission inhibits the ability to fully investigate possible anticipatory behavior. If water right owners were anticipating the shift in the call regime and took action prior to its realization, the parallel trends assumption would not hold and our results could be biased. Figure A5, Figure A6, and Figure A7 present coefficient estimates with 95% confidence intervals for the main econometric models (Table 2) with reference years 1976, 1987, and 1997, respectively. For the Flood Acres, Sprinkler Acres, and Sprinkler % models, results do not change qualitatively across reference years and pre-treatment coefficient estimates are consistently insignificant. Most importantly, the insignificant coefficient estimates for 2001 indicate no substantial behavioral differences between treatment and control diversion structures in the year immediately preceding the shock.

Lastly, we discuss the model specification, in particular the choice of year fixed effects versus a drought severity control variable (e.g., PDSI) across our study area. Localized weather conditions influence crop water demands as well as the amount of effective precipitation available to plants. As with much of the American West, the timing and quantity of surface water supplies available to producers for irrigation is based largely on winter (quantity of snow) and spring/early summer (timing of snowmelt) weather conditions in the mountains outside of our study area (as much as 200 miles away from the planting location and/or in another river basin). While PDSI is an effective measure of long-term (18 month) drought, it reflects local conditions. Within a time period, there is little variation across our study area, and the variation that does exist would not explain differences in surface water availability across producers (or the exogenous shock to perceived water right reliability that we observe). Our goal in this paper is to identify the effect of changing perceptions about surface water availability on producer behavior. Including year fixed effects allows us to estimate the effect of the unexpected shortages beginning around 2002 while controlling for differences in weather conditions (along with market conditions and any other factors constant across space) that may exist across the study period.

Nonlinear Impacts of Changing Perceptions

From the theoretical model, we determined that changing perceptions can impact adoption nonlinearly depending on the movement of θ and δ. The increase in expected gross benefit from an increase in θ could potentially be nullified by either an increase or decrease in δ, depending on the starting combination. Looking again at the right-hand column of figure Figure A1, we would expect treated units that moved to the lightest areas to have higher rates of adoption. We investigate this hypothesis informally by imposing total changes in sprinkler acreage (Figure A8) and sprinkler acreage as a percentage of total acreage (Figure A9) for each structure on the bottom right panel of Figure A1.[10] 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.

[10]Change in sprinkler acreage as a percentage of total acre is calculated as a difference in percentage points.

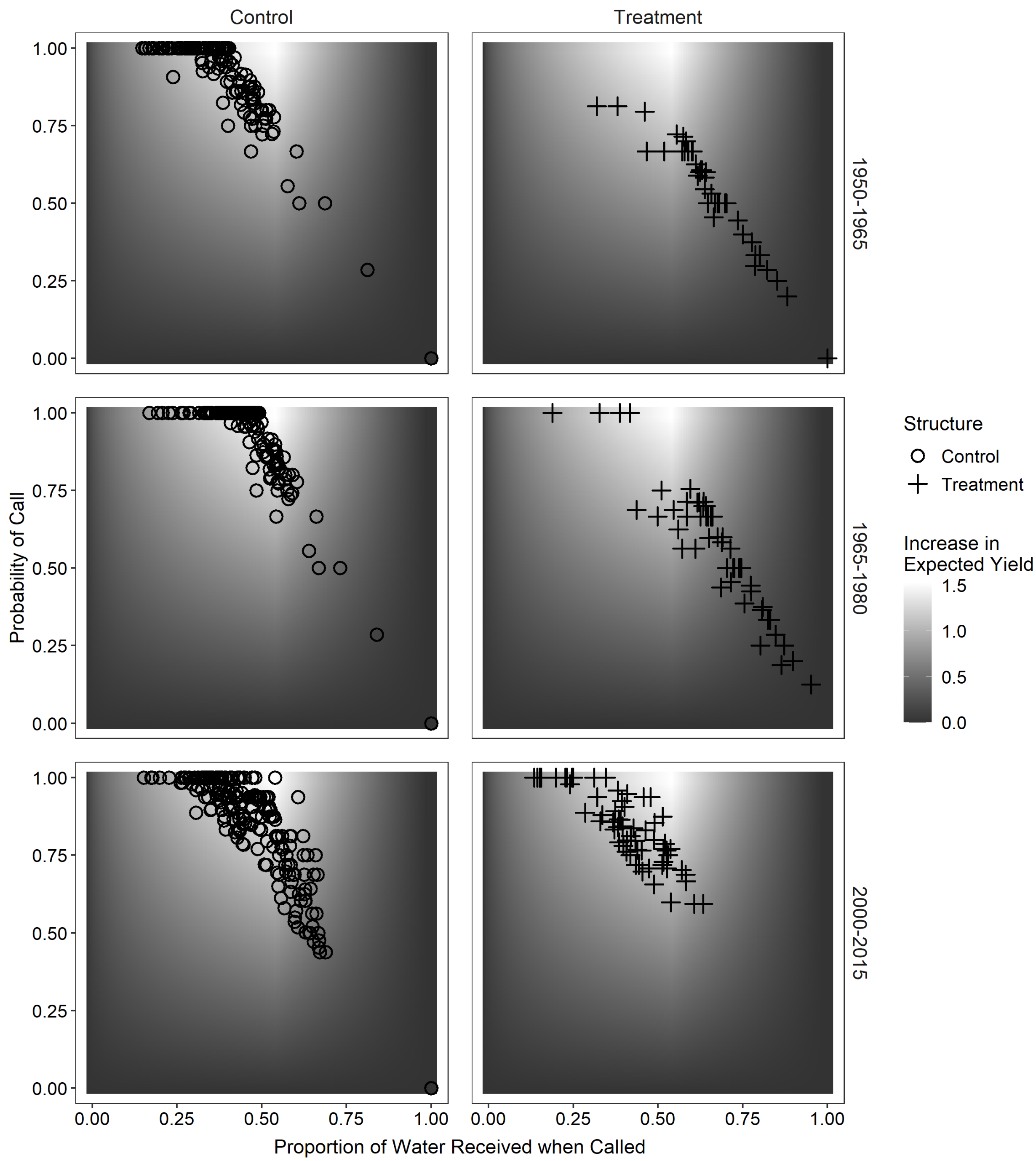

Figure A1: Estimated Perception Parameters for Control versus Treatment Diversion Structures

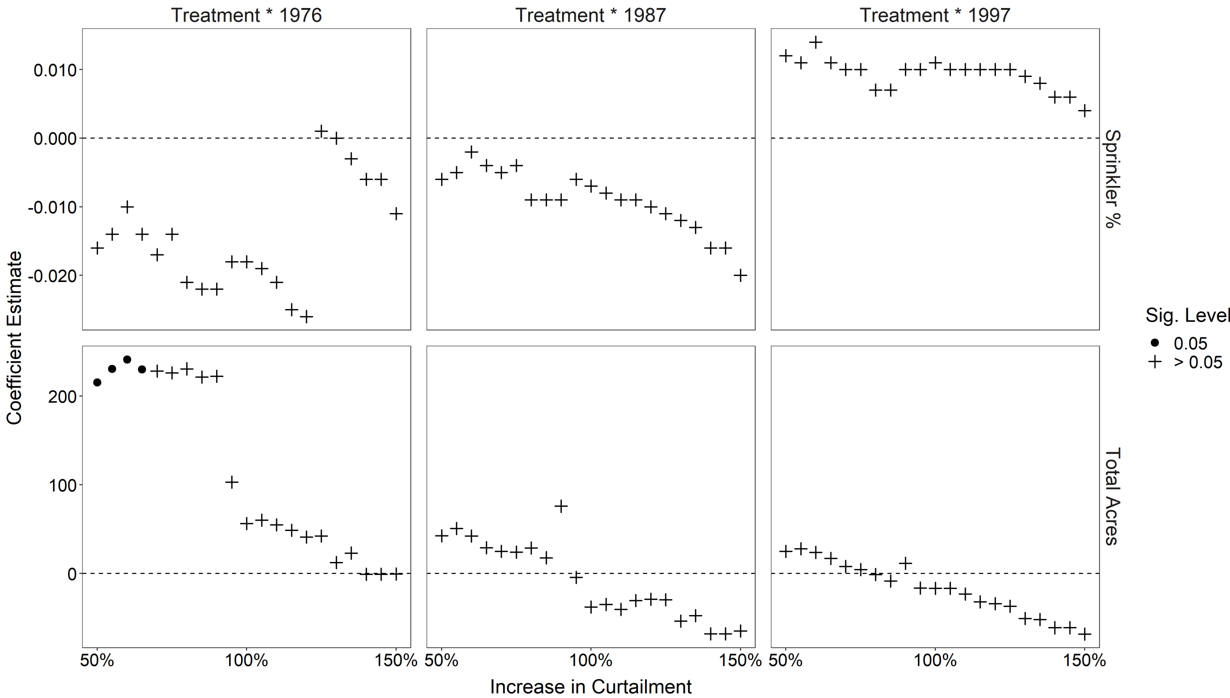

Figure A2: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Pre-Treatment

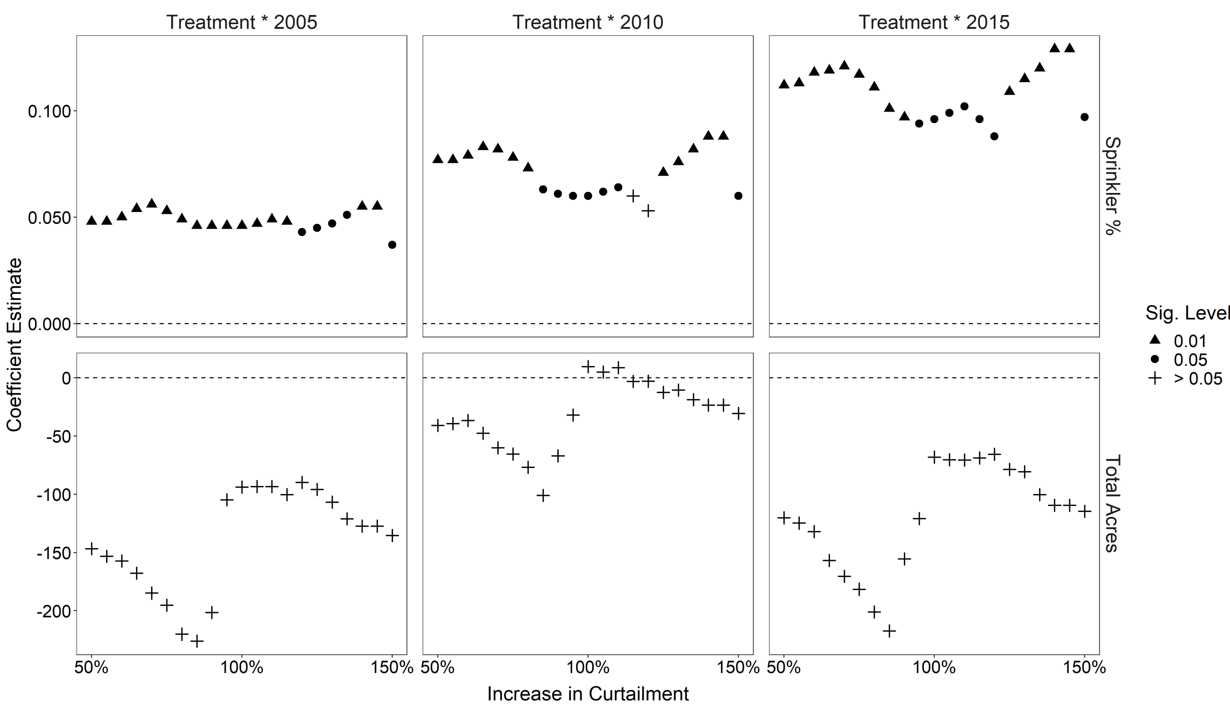

Figure A3: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Post-Treatment

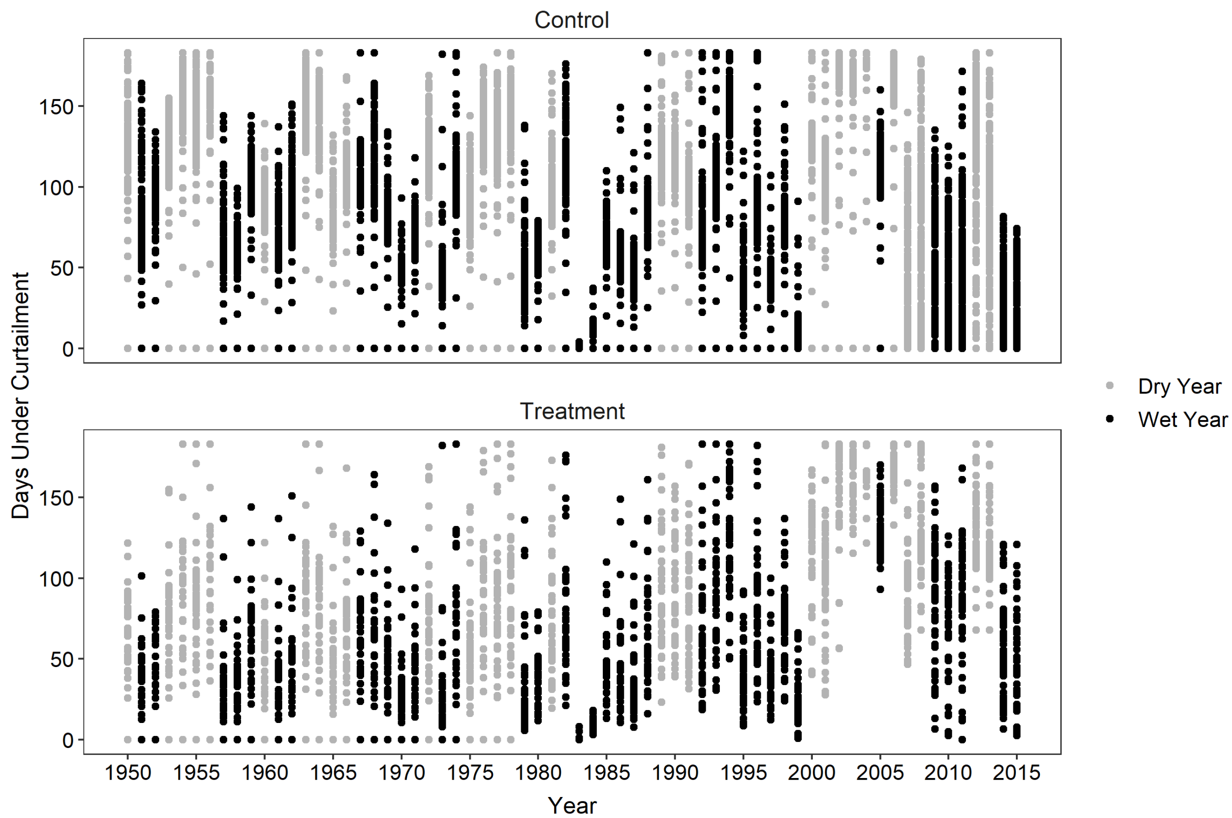

Figure A4: Average Days Under Curtailment for all Treatment and Control Structures by Year

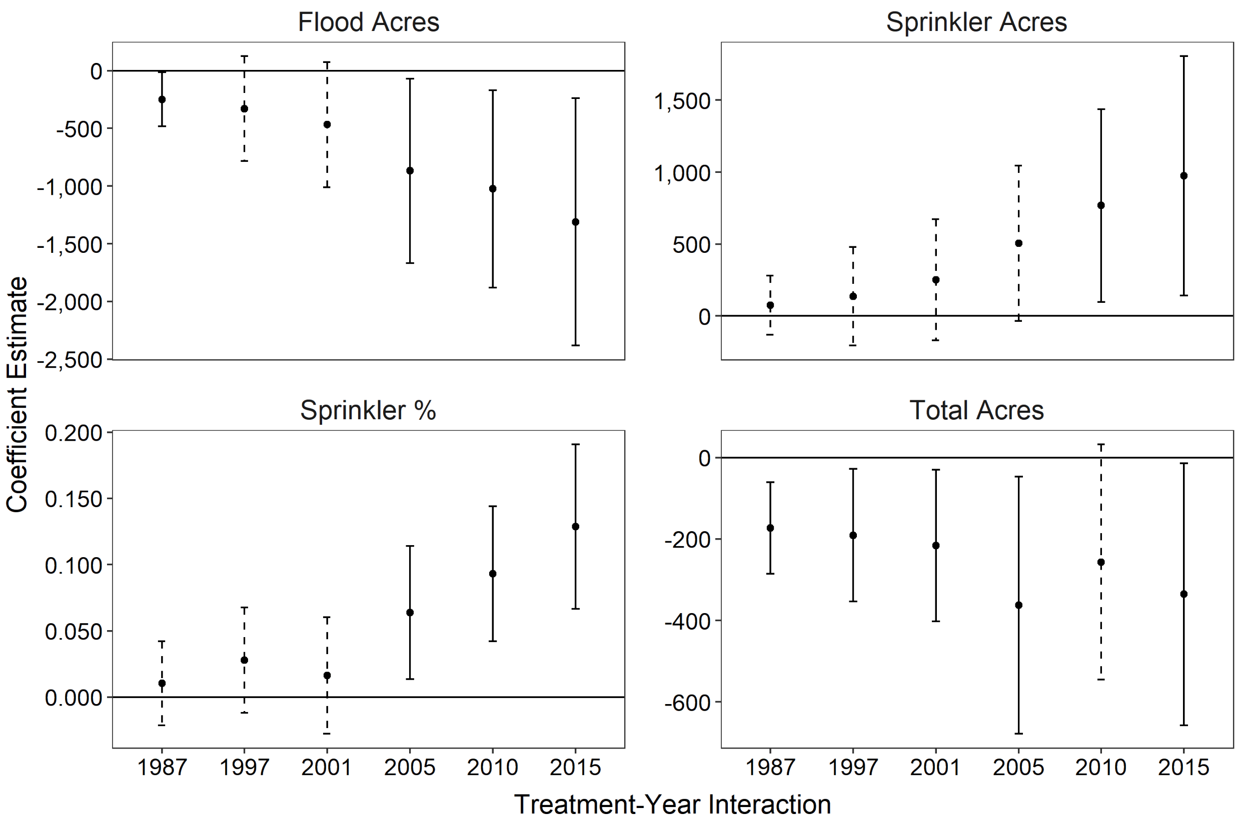

Figure A5: Difference-in-Difference Estimations, Reference Year 1976

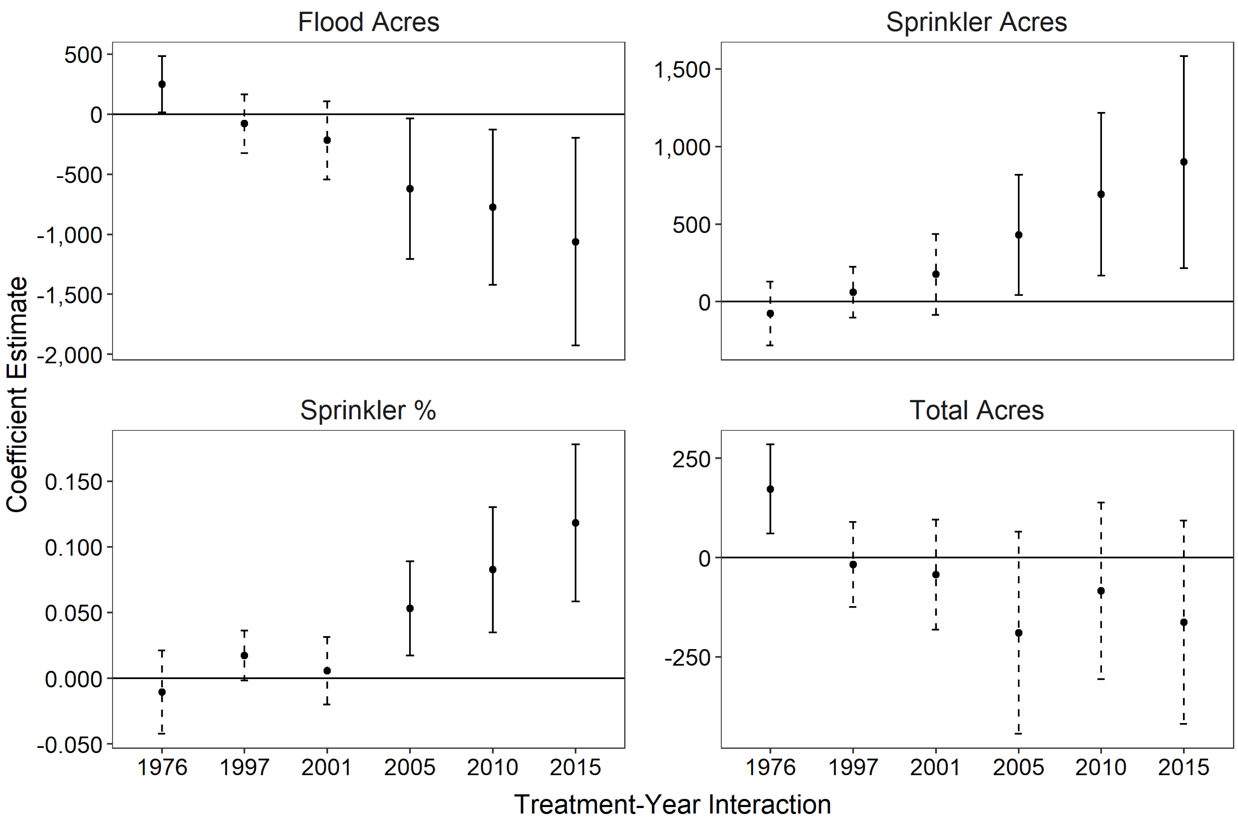

Figure A6: Difference-in-Difference Estimations, Reference Year 1987

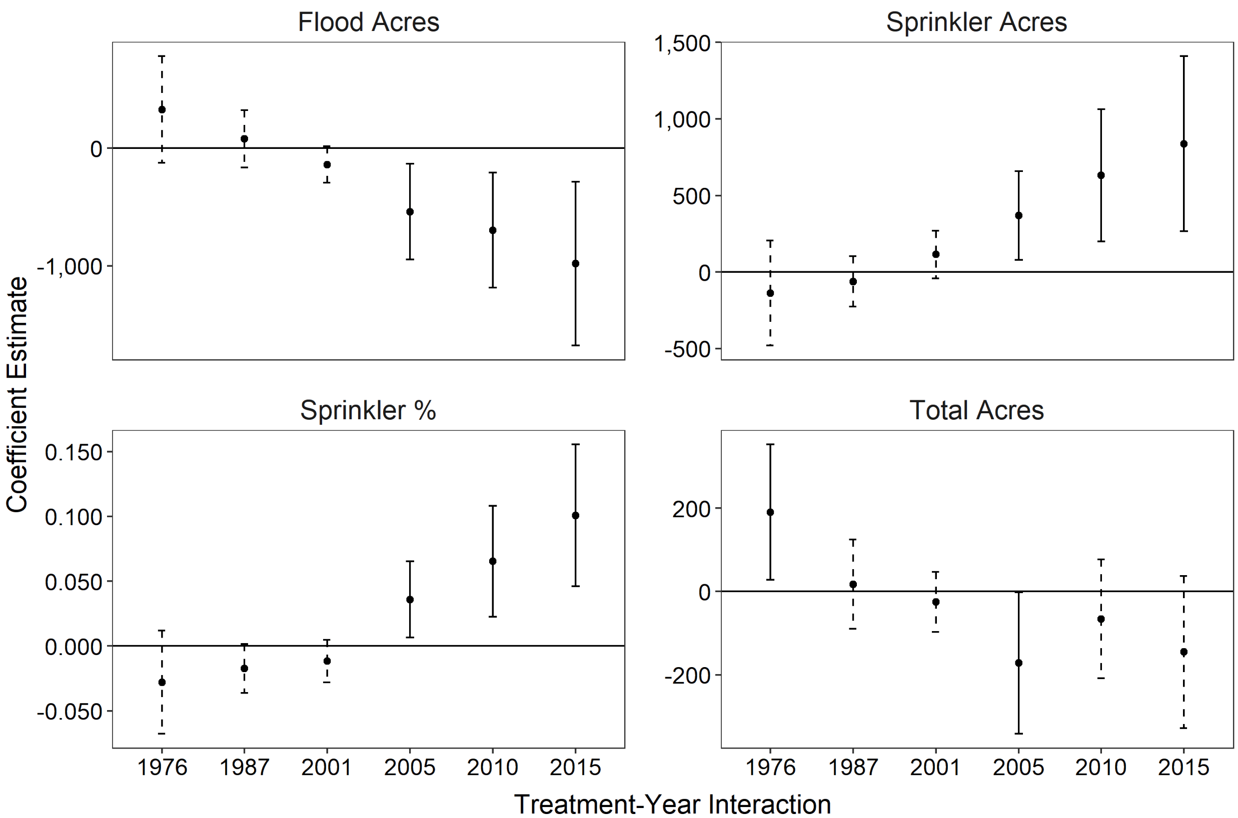

Figure A7: Difference-in-Difference Estimations, Reference Year 1997

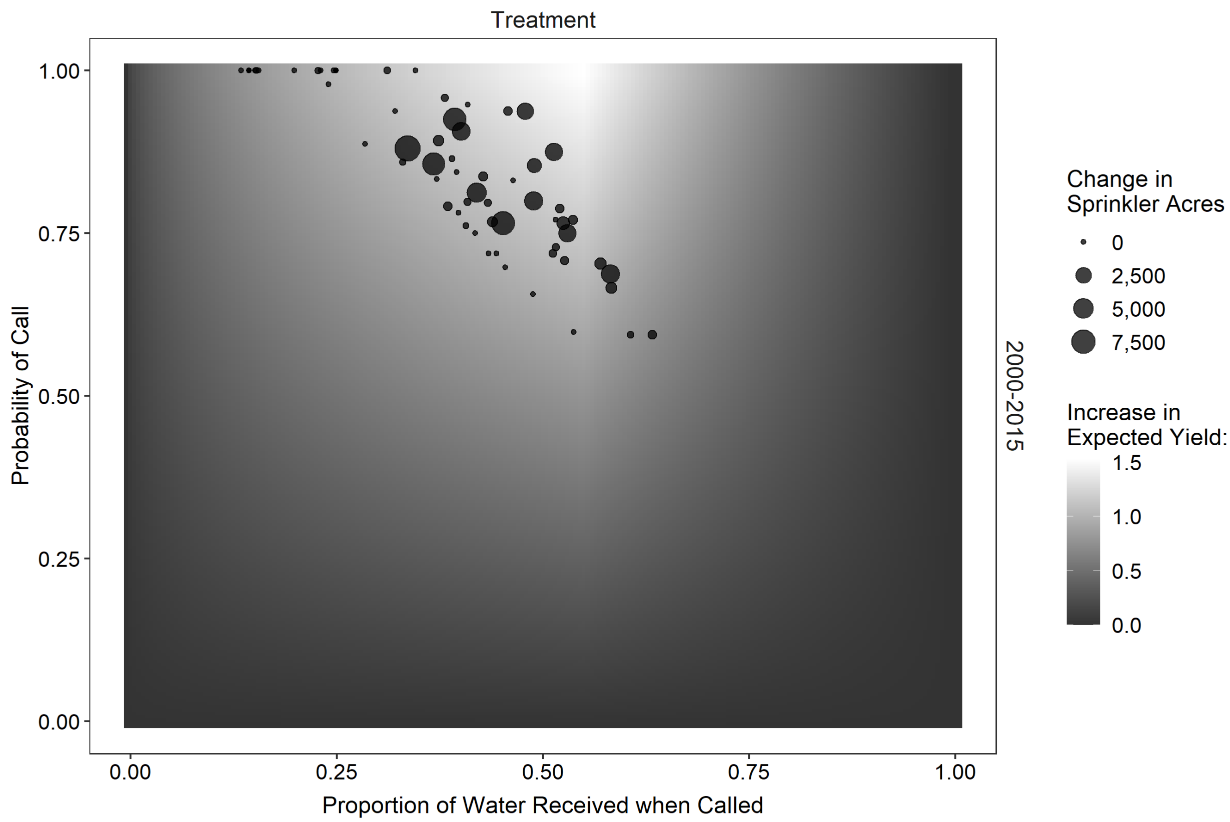

Figure A8: Nonlinear Impacts of Perceptions on the Adoption of Sprinkler Technology, Total Sprinkler Acreage

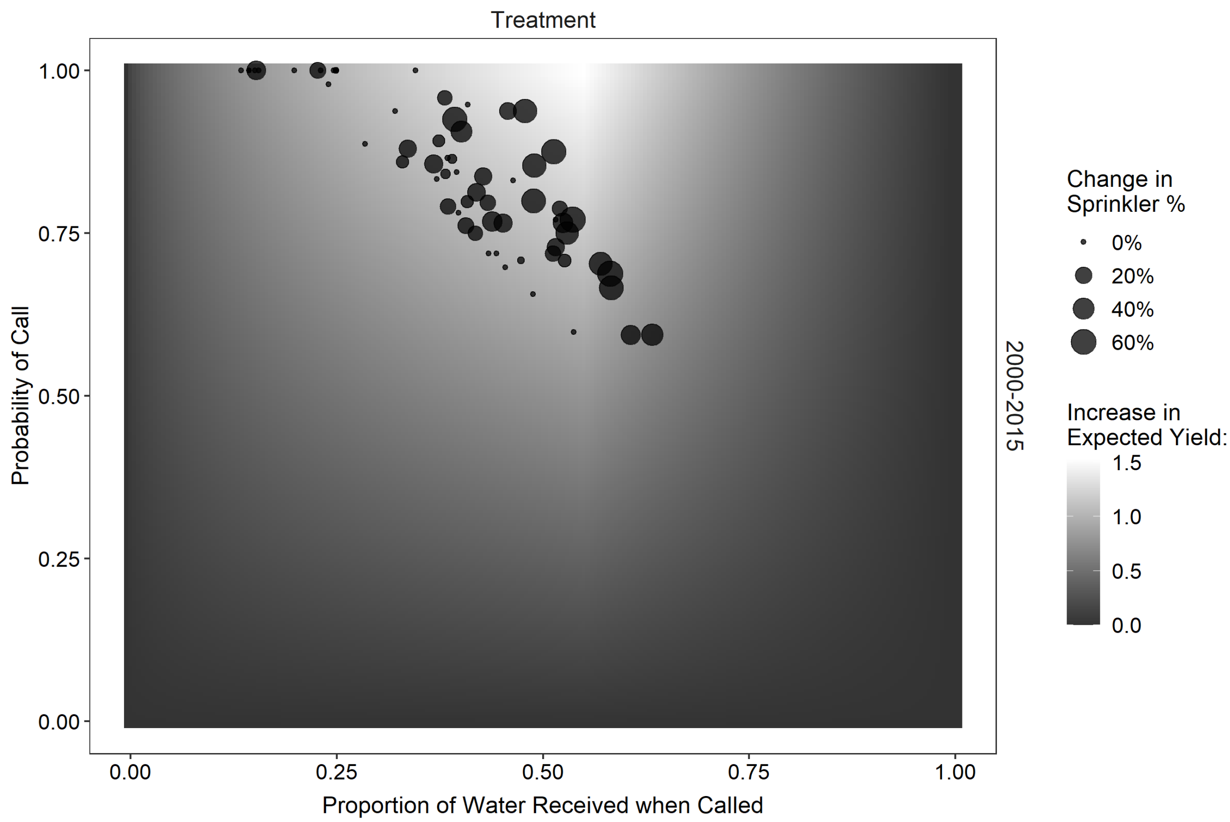

Figure A9: Nonlinear Impacts of Perceptions on the Adoption of Sprinkler Technology, Sprinkler Acreage as a Percentage of Total Acreage