Data appendix for "Perceived Water Scarcity and Irrigation Technology Adoption," by Joey Blumberg, Chris Goemans, and Dale Manning. In *American Agriculture, Water Resources, and Climate Change*, edited by Gary D. Libecap and Ariel Dinar. University of Chicago Press, 2023. https://www.nber.org/books-and-chapters/american-agriculture-water-resources-and-climate-change

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 $\left(1 - \frac{\text{days under curtailment}}{\text{growing season days}}\right)$ 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 treat-ment 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.

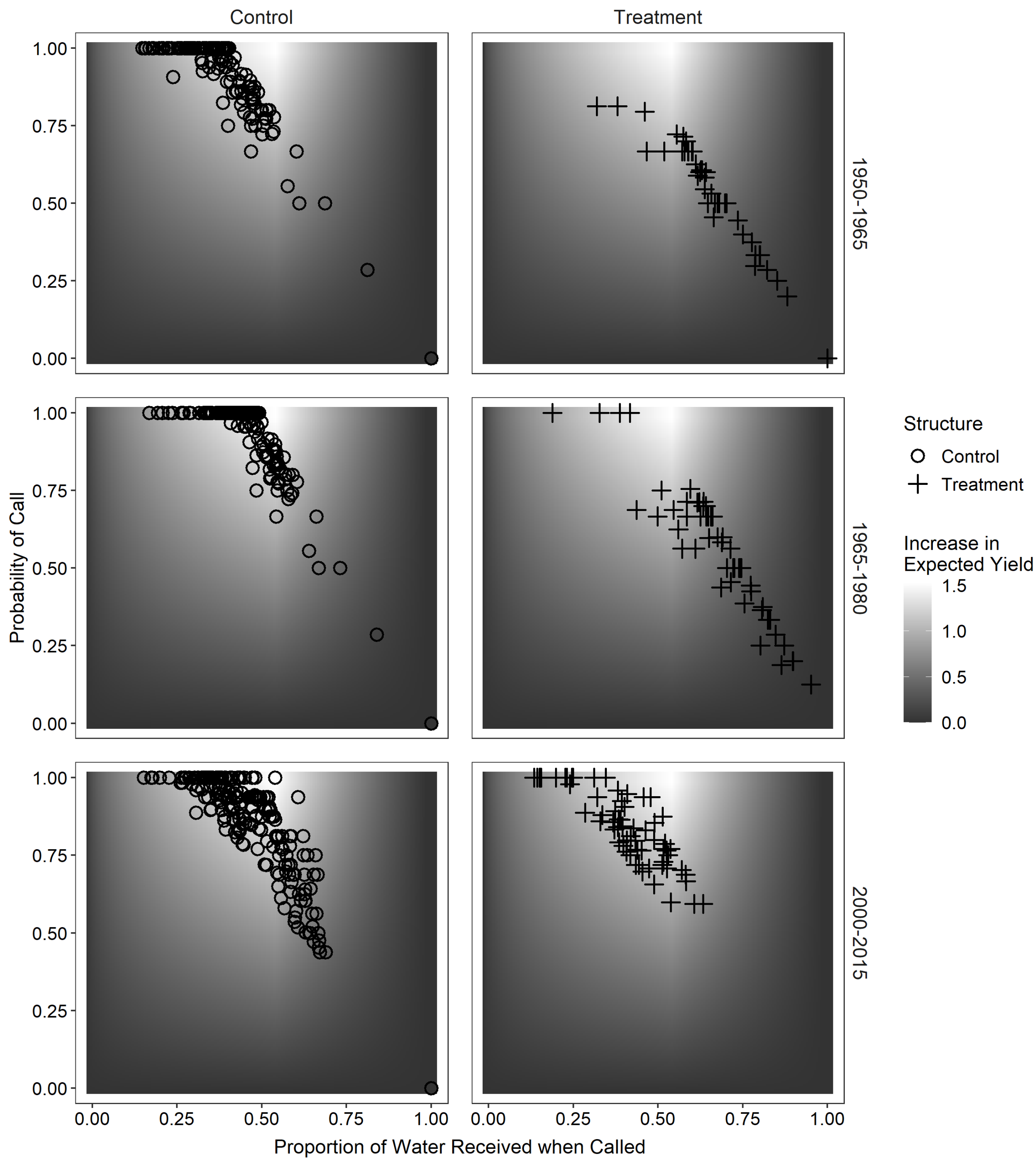

Figure A1: Estimated Perception Parameters for Control versus Treatment Diversion Structures

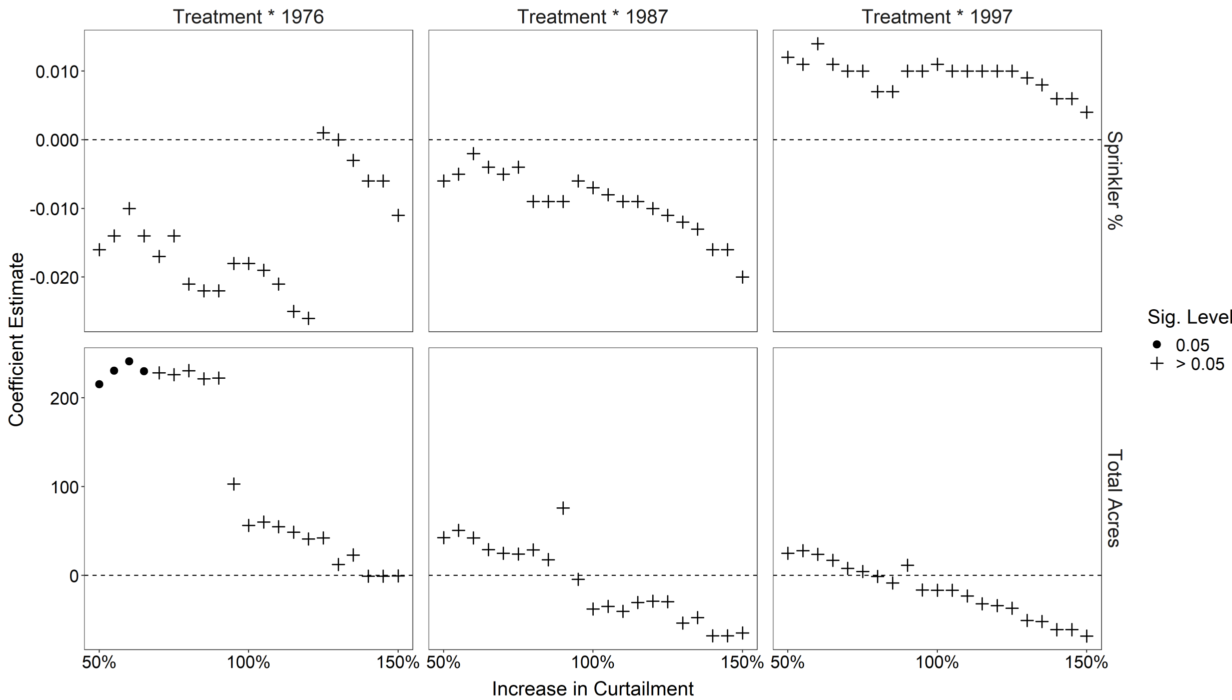

Figure A2: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Pre-Treatment

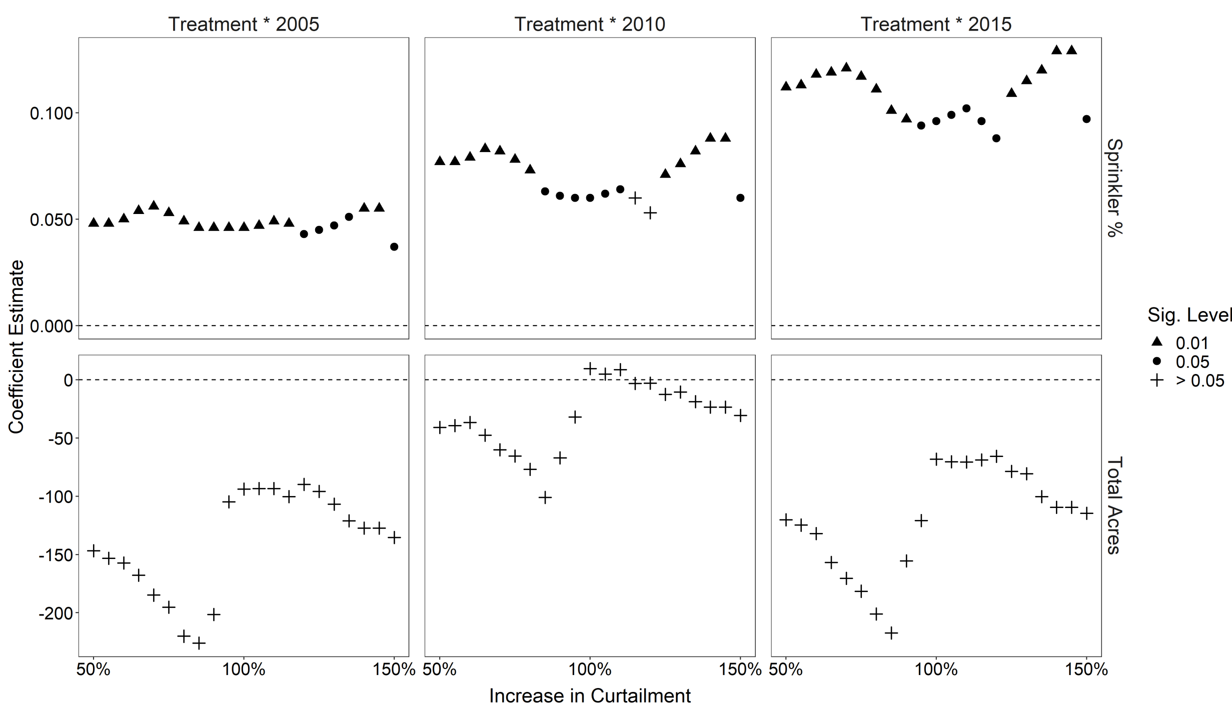

Figure A3: Robustness of Difference-in-Difference Estimations to Cutoff Selection, Post-Treatment

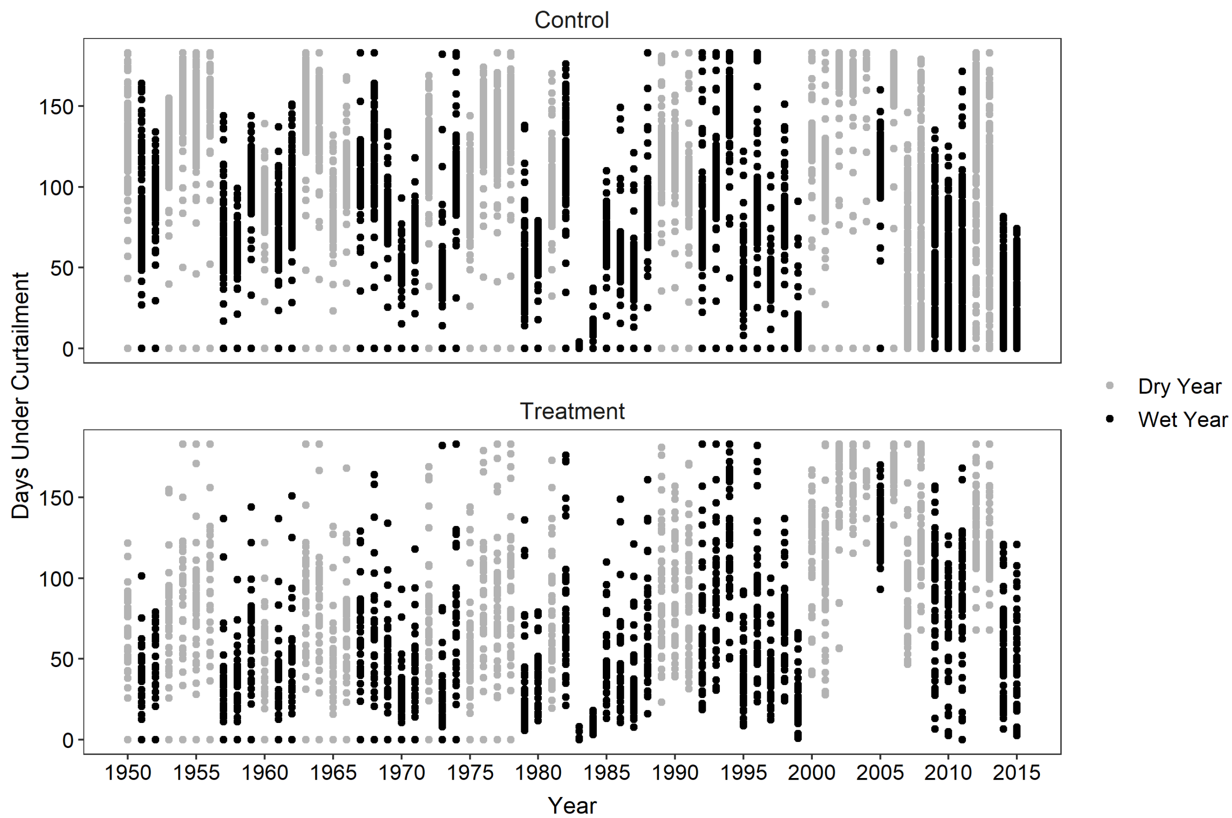

Figure A4: Average Days Under Curtailment for all Treatment and Control Structures by Year

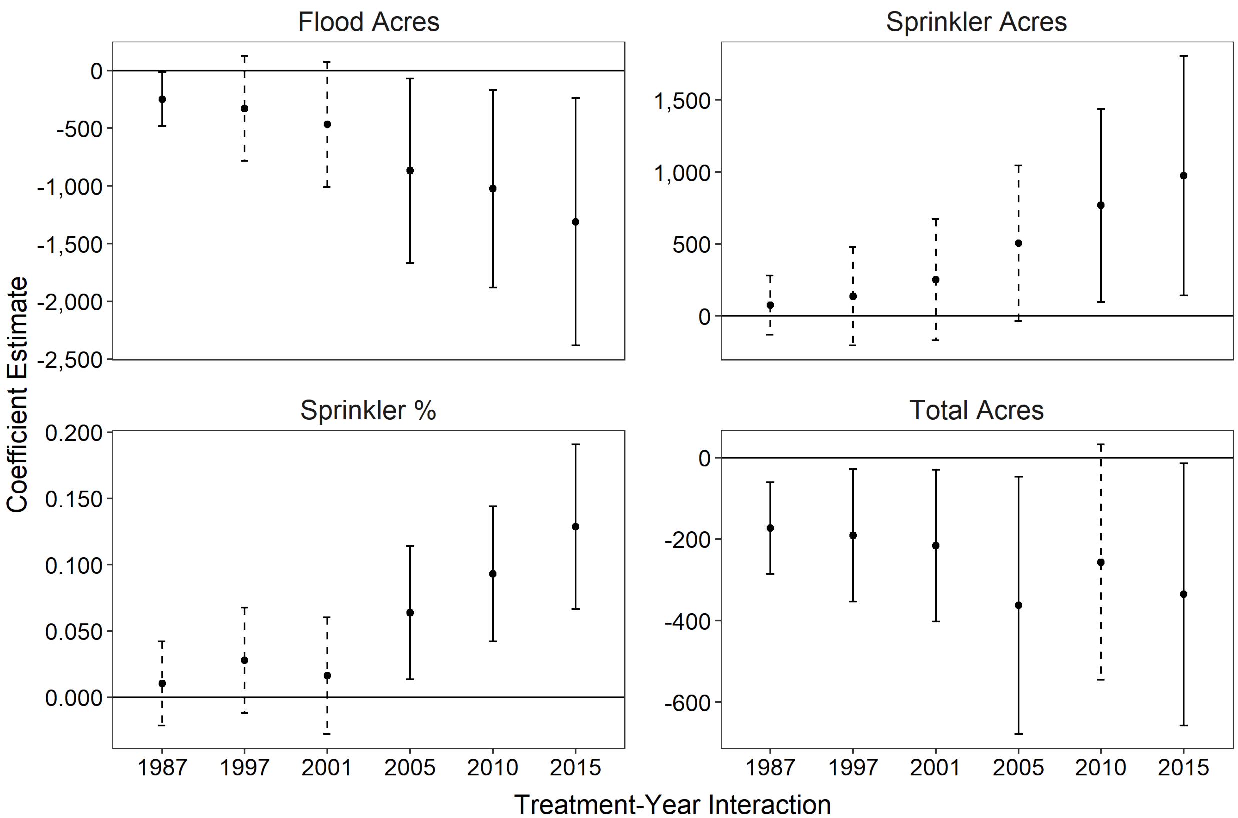

Figure A5: Difference-in-Difference Estimations, Reference Year 1976

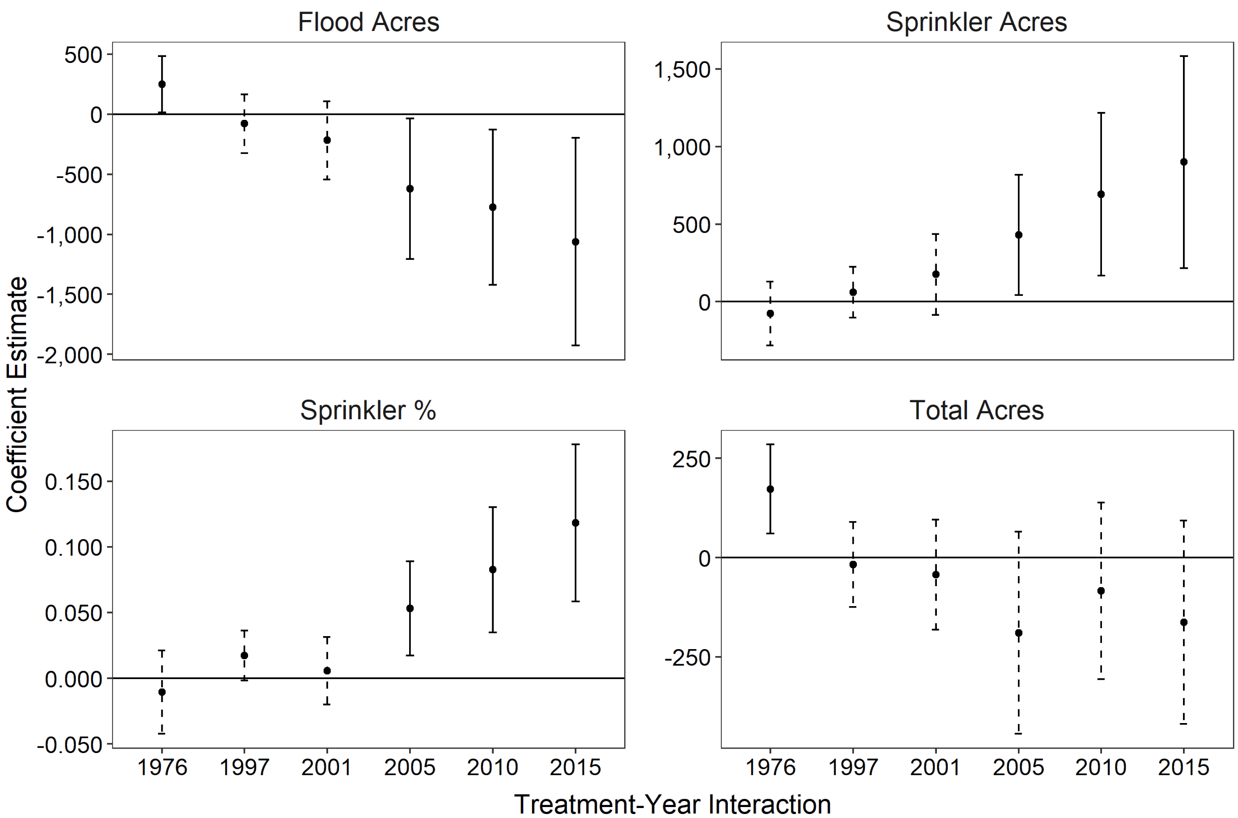

Figure A6: Difference-in-Difference Estimations, Reference Year 1987

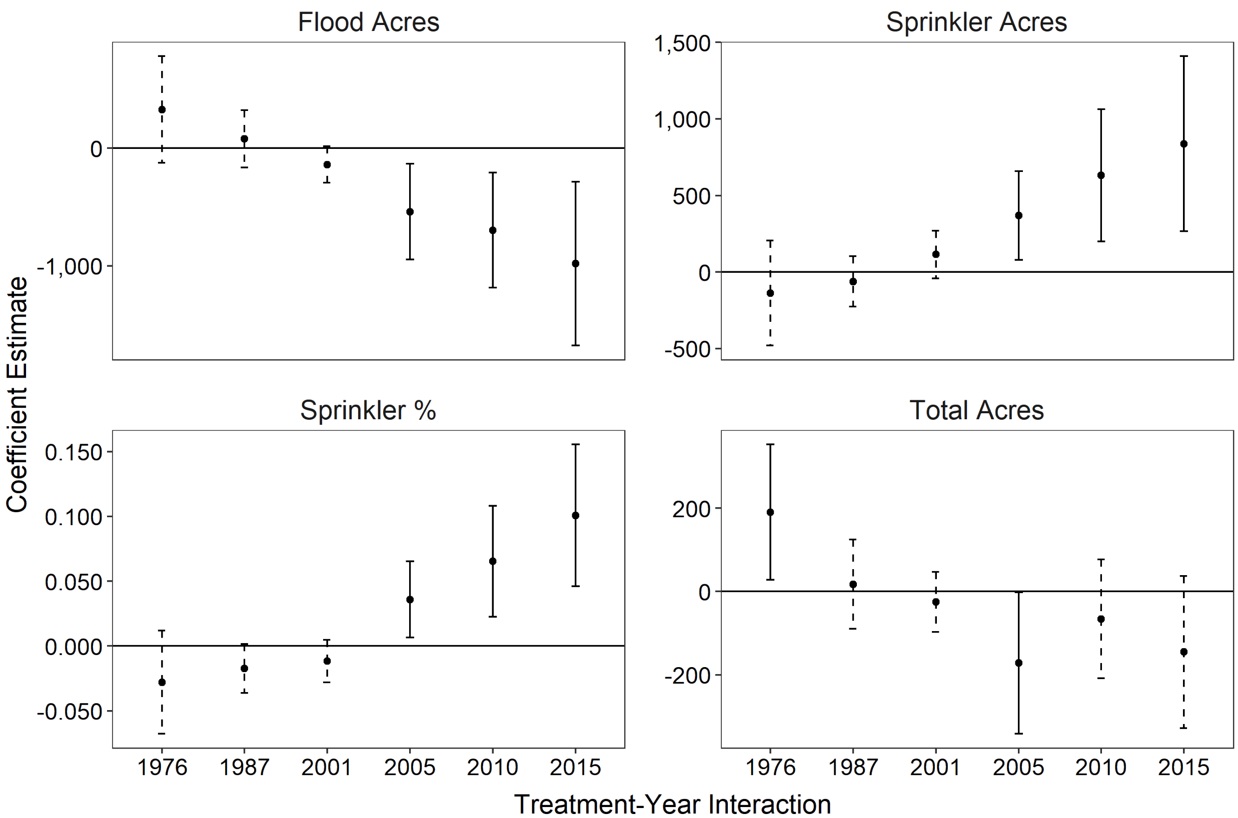

Figure A7: Difference-in-Difference Estimations, Reference Year 1997

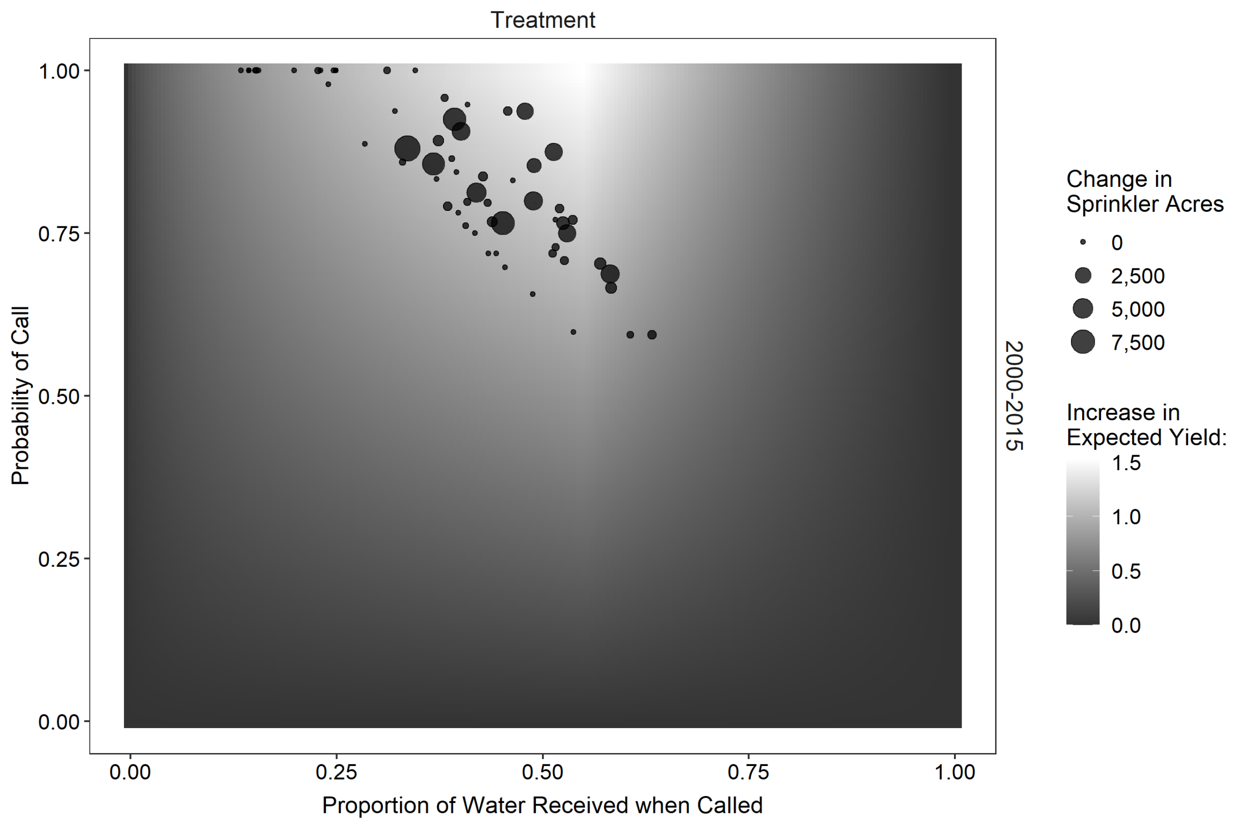

Figure A8: Nonlinear Impacts of Perceptions on the Adoption of Sprinkler Technology, Total Sprinkler Acreage

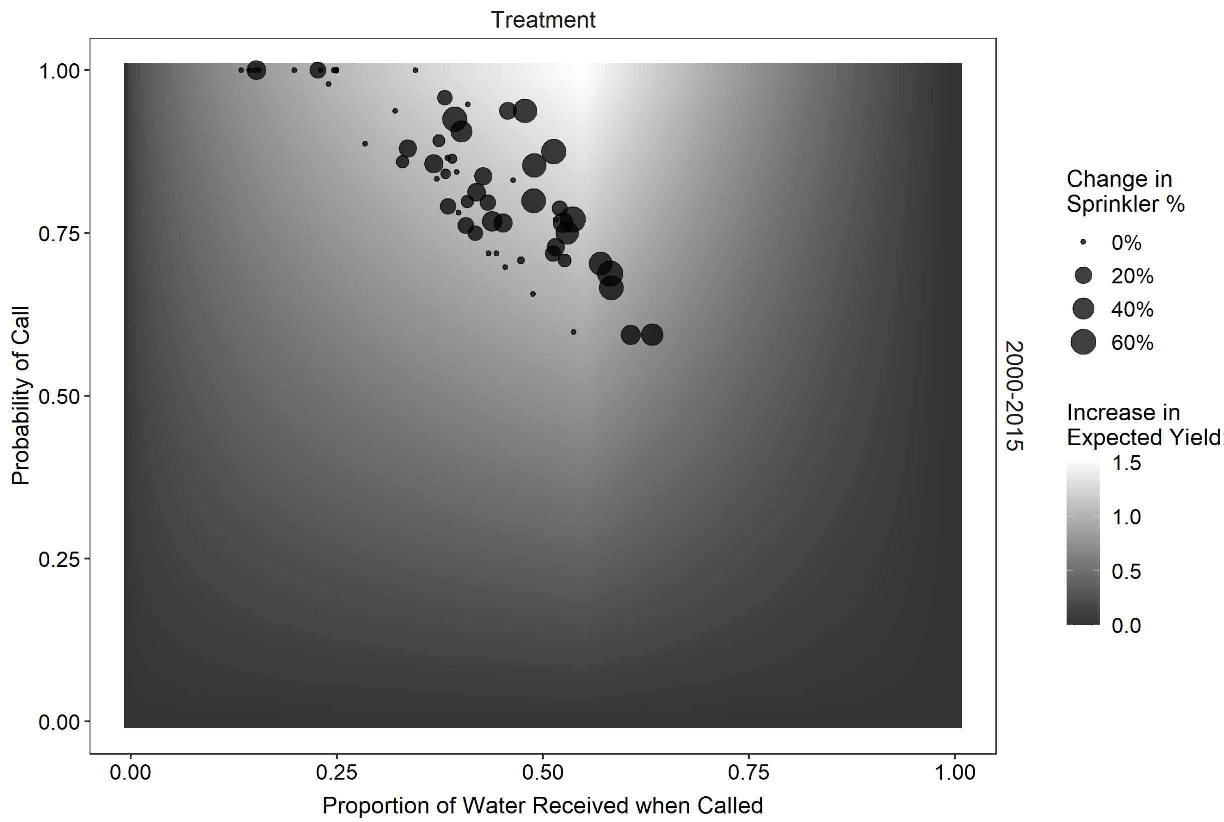

Figure A9: Nonlinear Impacts of Perceptions on the Adoption of Sprinkler Technology, Sprinkler Acreage as a Percentage of Total Acreage